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Automatability of occupations, workers' labor-market expectations, and willingness to train*

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Abstract

We study how beliefs about the automatability of workers' occupation affect labor-market expectations and willingness to participate in further training. In our representative online survey, respondents on average underestimate the automation risk of their occupation, especially those in high-automatability occupations. Randomized information about their occupations' automatability increases respondents' concerns about their professional future, and expectations about future changes in their work environment. The information also increases willingness to participate in further training, especially among respondents in highly automatable occupation (+five percentage points). This uptick substantially narrows the gap in willingness to train between those in high- and low-automatability occupations.

Keywords: automation, further training, labor-market expectations, survey experiment, information

JEL classification: J24, O33, I29, D83

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1. Introduction

Technological progress is a key driver of economic growth (Acemoglu 2009; Jones 2002; Aghion and Howitt 1992). Changes in technology often bring about drastic changes in the demand for different input factors. One notable example is the ongoing digital transformation: technologies like artificial intelligence have already transformed the skill demand in many professions, rendering existing skills and sometimes entire professions obsolete (OECD 2021; Dachs 2018; OECD 1998). At the same time, there is an increasing demand for occupations and skills that complement new technologies.[1] Because of these new and changing technological opportunities and the rising automatability of occupations, the knowledge that workers have acquired becomes outdated at an ever-faster rate. Therefore, further training throughout one's working life is crucial for workers to keep pace with, and benefit from, structural change on the labor market (e.g., Innocenti and Golin 2022; Bessen 2019).

In this paper, we study whether workers are aware of their occupations' automatability, and how factual information about occupations' automatability affects labor-market expectations and willingness to participate in further training. Workers in occupations with high automatability are strongly underrepresented in further training initiatives in many countries (Heß et al. 2019; OECD 2021), whereas their employment prospects would benefit most from further training.[2] The inequality in further-training participation between individuals in high- and low-automatability occupations is not yet fully understood. Based on the observation that people are often misinformed about labor-market relevant facts, like their probability to find a new job, wages, or outside options (Jäger et al. 2021; Mueller et al. 2021), we hypothesize that workers' misperceptions about their occupations' automatability may contribute to low training participation of workers in high-automatability occupations.[3] If workers underestimate their occupations' automatability, they may underinvest in keeping their skills up-to-date,

[1] For Germany, the country we study, the Federal Ministry of Labour and Social Affairs estimates that 5.3 million jobs will be lost by 2040, while 3.6 million new jobs will be created (Bundesministerium für Arbeit und Soziales, 2021).

[2] Several studies show that workers in high-automatability occupations have worse employment outcomes and lower wage growth, which highlights the importance of studying their obstacles to participating in further training (Georgieff and Milanez 2021; Montobbio et al. 2022; Acemoglu and Restrepo 2020b; Schmidpeter and Winter-Ebmer 2021; Dauth et al. 2021).

[3] Complementary reasons for non-participation in further training include, e.g., stigmatization (since further training possibilities are sometimes offered by the Federal Employment Agency, which most people in Germany associate with unemployment), failure to recognize potential benefits, high costs, or lack of time resources (e.g., van den Berg et al. 2019; Müller and Wenzelmann 2020; Osiander and Stephan 2020). We report further details on barriers to participation in section 4.3.

potentially jeopardizing their labor-market success amidst ongoing labor-market transformations.

Previous literature has mostly focused on the effects of automation on labor-market outcomes. In contrast, little is known about how workers perceive their occupations' automatability, and how these beliefs affect labor-market expectations and willingness to train. We address this gap by (i) documenting beliefs about automatability in an online sample of the German population and (ii) studying experimentally how providing information about their occupations' automatability affects workers' beliefs, labor-market expectations, and attitudes towards further training. By examining the effects of randomized information provision, we can isolate the causal impact of correcting potentially biased beliefs on workers' expectations and willingness to training.

We implemented our experiment in a large online survey (N=3,012) to represent the German adult population. In the survey, we first elicited respondents' prior beliefs about the automatability of their occupations. We then provided the randomly selected treatment group of respondents with personalized information about their occupations' automatability. The remaining respondents served as the uninformed control group. We drew the information about occupations' automatability from the "IAB-Job-Futuromat" (https://job-futuromat.iab.de/) of the Research Institute of the Federal Employment Agency (IAB). The IAB-Job-Futuromat calculates each occupation's automatability by determining the share of its core tasks that could potentially be performed fully automatically, either by a computer or computer-controlled machine, according to expert evaluations (Dengler and Matthes 2018a). Finally, we measured (i) respondents' labor-market expectations about their professional future, (ii) their likelihood to participate in further training (e.g., skill enhancement programs) and retraining (i.e., career transition courses) and (iii) their willingness to accept a reduced wage during their further training period. By comparing responses between the uninformed control and the informed treatment group, we evaluate how factual information about the automatability of workers' occupations affects these outcomes.

We find that, on average, respondents underestimate the automatability of their own occupation. Crucially, the misperception is particularly large for those in occupations with high automatability. Descriptively, within the control group, respondents who believe that their occupations' automatability is low state the lowest likelihood of participating in further training. Furthermore, there is a positive correlation between respondents' beliefs about their occupations' automatability and their likelihood to participate in retraining. The information experiment allows us to investigate how exogenously shifting beliefs about automatability causally affects our outcomes of interest.

Experimental results show that information provision about the automatability of one's occupation affects labor-market expectations. Respondents become 9.7 percent of a standard deviation more concerned about their future work and are more likely to expect changes in their work environment (+13.0 percent of a standard deviation). Furthermore, the information treatment increases the stated likelihood of participating in further training and retraining by 5.8 and 12.5 percent respectively, relative to the mean. It also increases the fraction of wages that respondents are willing to forgo to participate in further training.

In line with our findings on misperceptions, the treatment effects for respondents in occupations with high automatability are larger than those with low automatability. Control-group respondents with high automatability express a 37.6 percent likelihood that they will participate in further training. Treated respondents in these occupations state a 4.6 percentage points (5.2 percentage points) higher likelihood to participate in further training (retraining). Conversely, for those in low-automatability occupations, the treatment effects on these outcomes are minimal and not statistically significant at -0.1 and 1.5 percentage points. Taken together, information provision reduces the control-group gap in the willingness to participate in further training between those in high- and low-automatability occupations by 95.5 percent, and fully closes the gap in willingness to participate in retraining. The same pattern emerges when considering respondents' willingness to accept a reduced wage to participate in further training. These findings suggest that misperceptions regarding occupations' automatability significantly contribute to the observed low training participation rates among workers in occupations most susceptible to technological change and automation.

Further results show that reluctance to participate in further training is not due to ignorance of the benefits. A large majority (76.7 percent) of respondents agree that further training is useful for keeping pace with structural change. Similarly, 66.2 percent agree that the future need for further training will increase for all employees, and 62.5 percent agree that everyone affected by structural change should participate in further training. Respondents state that the main reasons for not participating in further training are financial constraints (45.4 percent), lack of employer support (45.0 percent), and time constraints (35.2 percent). Answers on these outcomes are unaffected by treatment-group status. Treated respondents also request additional information about further training programs and finance options at the same rate as respondents in the control group.

The remainder of this paper is structured as follows. Section 2 provides an overview of the existing literature. Section 3 presents the institutional background, the study setup, and the empirical strategy. Section 4 presents descriptive and experimental results. Section 5 concludes.

2. Related Literature

Our study contributes to several strands of the existing literature. First, we relate to the literature on the effects of technology and automation on labor-market outcomes. Existing studies in this field have predominantly used non-survey data to examine the impact of automation on employment and wages. Acemoglu and Restrepo (2018, 2020a) highlight two key effects of new technologies on jobs and wages: the displacement effect, where robots replace human tasks, and the productivity effect, boosting productivity and thereby increasing labor demand in non-automated roles, leading to new jobs and tasks (Acemoglu and Restrepo 2019).[4] Several studies have empirically examined the effect of (industrial) robots on employment outcomes (Acemoglu and Restrepo 2020a; Graetz and Michaels 2018; Autor and Salomons 2018; Dauth et al. 2021). Most studies find no effect on total employment and a positive impact on productivity and wages (Graetz and Michaels 2018; Dauth et al. 2021).[5] The overall zero employment effect can mask substantial displacement and re-allocation effects (Arntz et al. 2020; Dauth et al. 2021)). Considering these findings, some researchers suggest automation may cause more worker transitions than mass unemployment (Bessen et al. 2020). Nonetheless, whether transitioning workplaces or facing unemployment, workers need to retrain, often learning new skills and switching occupations or industries. Participation in further-training programs is therefore vital for ensuring matching of labor demand and supply in rapidly changing labor markets. We contribute to this literature by using survey data and focusing specifically on the link between workers' beliefs about automatability and their labor-market expectations, as well as their willingness to (re)train.

Second, our paper adds to the literature that examines how workers (with varying skill levels) respond differently to technological change. For example, Blanas et al. (2019) argue

[4] Recent studies on the emergence of "new work" and the task-based approach discuss how automation and computerization reallocate many human tasks to machine tasks, expanding the set of tasks performed by capital (Acemoglu and Restrepo 2022), and how they complement educated workers (Autor 2022). The introduction of new job tasks or job categories requires specialized human expertise, more education and workforce training (Autor et al. 2022; Autor 2022).

[5] An exception is the paper by Acemoglu and Restrepo (2020a), which finds negative effects of robots on employment and wages across U.S. commuting zones.

that some workers respond to automation by transitioning to low-paid occupations where tasks are difficult to replace with machines, while other workers acquire new skills that complement machines and allow them to work in high-paid occupations. Cortes (2016) examines the effects of routine-biased technical change[6] on workers' occupational transitions and wages, finding that especially low-ability routine workers tend to switch to non-routine manual tasks, while high-ability routine workers switch to non-routine cognitive occupations. We add to this literature by investigating how workers' misperceptions about the automatability of their occupations – a factor not previously studied – contributes to lower skill investments, especially among workers in high-automatability occupations. Other studies have examined barriers to training participation, such as misjudgment of potential benefits, high costs, or lack of time resources (e.g., van den Berg et al. 2019; Müller and Wenzelmann 2020; Osiander and Stephan 2020). We complement this by explicitly focusing on differences in participation rates across subgroups of workers and examining the influence of workers' beliefs about automatability on their willingness to train.

Moreover, our study relates to the literature on the relationship between automation and further training. Heß et al. (2019) find that further-training participation strongly varies with the level of routine tasks in employees' occupations: workers with the most routine tasks participate less (27 percent) compared to those with fewer routine tasks (41 percent). Innocenti and Golin (2022) show that 30 percent of respondents in their international sample are worried about being replaced by machines or algorithms and that workers' fear of automation is positively associated with their intentions to invest in training activities. Nedelkoska and Quintini (2018) use data from the Programme for the International Assessment of Adult Competencies (PIAAC) and find that workers in occupations at risk of automation have lower on-the-job and outside training participation rates. While these studies are primarily descriptive, we add to the literature by experimentally examining the causal link between automatability perceptions and further-training participation.

Methodologically, our paper relates to the literature leveraging survey experiments to examine how information affects public preferences (e.g., Cruces et al. 2013; Kuziemko et al. 2015; Bursztyn 2016). The experimental literature on information provision about automation and the future of work is closest to our study. Jeffrey (2021) shows that priming respondents

[6] Since the 1980s, technological changes have led to the occurrence of more machines and computers that mainly perform routine tasks. Therefore, mainly routine workers are substituted. This hypothesis is termed routine-biased technological change (Cortes 2016). Earlier literature hypothesized that technological change is skill-biased, which favored high-skilled workers without distinguishing between tasks and skills (e.g., Katz and Murphy 1992; Autor et al. 1998).

with the notion that automation could lead to unfair disruptions in the labor market can increase preferences for redistribution. Arntz et al. (2022) provide two pieces of aggregate information about labor-market effects of automation (i.e., no aggregate employment losses, employment shift from unskilled to skilled workers). They find that information about zero net employment effects reduces concerns about automation but does not affect stated labor-market behavior and donations to NGOs. In comparison to these studies, our contribution lies in providing respondents with personalized, occupation-specific information about the automatability of their occupation. Closest to our paper, Golin and Rauh (2022) study how informing respondents about their job-loss probability affects policy preferences and different labor-market intentions. We extend this evidence by (i) focusing on automatability more generally and (ii) providing an in-depth analysis of how this type of information affects different dimensions of workers' labor-market beliefs and training intentions. This is particularly relevant for many contexts where automatability leads to changes on the labor market that extend beyond unemployment.

3. Background, Study Setup, and Empirical Strategy

In this section, we present the institutional background of further training in Germany (section 3.1), our data source, the ifo Education Survey (section 3.2), the experiment (section 3.3), the econometric model (section 3.4), and the sample description (section 3.5).

3.1. Institutional Background

In Germany, the majority of all further-training activities (72 percent) take place within the company (BMBF 2018). The average duration of in-company further training is 29 hours per training, which is shorter than the average individual job-related training outside the company (153 hours per training) (BMBF 2018). Based on the ifo Education Survey 2022, which serves as our data source (see section 3.2), 63 percent of respondents reported past participation in further training, revealing that over one third (37 percent) had not engaged in any additional training.

Overall, there are approximately 18,000 public and private further training providers (Bundesinstitut für Berufsbildung 2020). The training sector is governed by a variety of regulatory levels and legal foundations, including collective bargaining agreements, company agreements, laws, and state-level regulations. The responsibility and financial burden for further training are shared among companies, workers, and the public sector. The 'Work-of-Tomorrow Law' (Arbeit-von-morgen-Gesetz), a new German regulation introduced in 2020, stipulates that further training exceeding 120 hours may receive subsidies from the Federal Employment Agency. Depending on the company's size, the Agency can finance up to 100 percent of the training costs. This law is specifically aimed at people with occupations that can be replaced by technology or are otherwise affected by structural change. For more information about the institutional background, see Appendix A.

3.2. Data

We use data from the ifo Education Survey 2022, a large-scale annual opinion survey on education policy in Germany (Freundl et al. 2022). The survey company Talk Online conducted sampling and polling of the online survey in May/June 2022. Overall, the survey encompassed questions related to education policy, focusing on topics related to structural change and lifelong learning.[7] In addition, we elicited sociodemographic background characteristics at the end of the survey. Median completion time is 16 minutes, and the item non-response rate is low, with a maximum of 2.9 percent for the questions used in this study. We restrict our sample to respondents who are currently employed. Since the sample was drawn to represent the German population using quotas for gender, age, state, education level, and employment status, our data cover a broad sample of the German working population from different occupational fields with different requirement levels (see section 3.4). The overall sample size is 3,012 respondents.

3.3. The Experiment

The experiment implemented in the ifo Education Survey provides respondents in the treatment group with personalized information about the automatability of their occupation. The experimental setup is as follows (see also Appendix Figure A1): first, we elicit respondents' current occupation and their beliefs about the automatability of their occupation (section 3.3.2). Next, we provide respondents in the treatment group with information about their occupations' automatability (section 3.3.1). Then, we elicit the main outcomes, i.e., labor-market expectations, likelihood of participating in further training and retraining, and the wage fraction they are willing to forgo during further training (section 3.3.3). Respondents in the control group answer the same questions without receiving the information. Finally, all respondents are asked about potential barriers to participating in further training.

[7] We define structural change to respondents in the following way: *By structural change, we mean the constant transformation of economic sectors accelerated by digital technologies, among other things.*

3.3.1. Information Treatment

We hypothesize that underestimation of the automatability of tasks contributes to low participation rates in further training for some subpopulations of workers. At the beginning of the survey, we ask respondents which occupation they currently work in.[8] According to respondents' occupations, the treatment provides personalized information about the automatability of the respective occupation to the randomly selected treatment group. We use occupation-level information on automatability from the "IAB-Job-Futuromat" (https://job-futuromat.iab.de/), provided by the Research Institute of the Federal Employment Agency (IAB).[9] The automatability ranges from zero to 100 percent. The information that we provide reads as follows: *According to a study, [X] percent of core tasks in occupation [answer from earlier question about current occupation] are as of today automatable.* The values in brackets are adjusted for each respondent according to his or her current occupation.[10] Along with the verbal statement, we also provide respondents with a graphical visualization of the information (see Appendix Figure A2). Previous research shows that this measure of automatability has important predictive power for employment growth (Dengler and Matthes 2018b).[11]

3.3.2. Eliciting Beliefs About Automatability

We elicit respondents' perceptions of the automatability of (i) their current occupation in general and (ii) their own job. Prior to the information treatment, we first ask the following

[8] Respondents can choose their occupation from a list of more than 4,000 occupations included in BERUFENET, an expert database for training and job descriptions from the German Federal Employment Agency. It is similar to the U.S. Occupational Information Network (O*NET).

[9] In order to obtain this measure of automatability, the IAB relies on a list of core tasks that are typically done by workers in each occupation. Subsequently, experts code for each of these tasks whether they could be fully automated with currently available technology (for details, see Dengler and Matthes (2018a) and https://job-futuromat.iab.de/faq.html). The "IAB-Job-Futuromat" data, reflecting technological capabilities as of 2019, align closely with our data collection period in May/June 2022. Notably, the widespread availability of large language models, such as ChatGPT, only began after our field phase, with its launch in November 2022. It is important to note that the concept of automatability is dynamic and will evolve with future technological innovations.

[10] For the treatment, we use information on general occupation-specific automatability, which is computed based on the assumption that workers in an occupation devote equal time to all core tasks. This assumption could lead to overestimating or underestimating an individual worker's automatability, contingent upon the actual time they spend on each core task (Dengler and Matthes, 2018b). Importantly, the information treatment explicitly clarifies that it provides insights into the automatability of the *occupation* as a whole, rather than the respondents' individual *jobs*.

[11] The approach by Dengler and Matthes (2018a, 2018b) is similar to the job-level (task-based) approach by Arntz et al. (2017), who estimate that about twelve percent of workers in Germany have an automation risk greater than 70 percent (Arntz et al. 2016). For the U.S., Arntz et al. (2016) calculate that approximately nine percent of workers work in jobs with an automation risk above 70 percent, which is lower than the occupation-level approach by Frey and Osborne (2017), who estimate that about 47 percent of jobs are at risk of automation.

question about the share of core tasks respondents think are automatable in their current occupation: *What do you think is the percentage of core activities that people perform in the profession [answer from earlier question about current occupation] that can be automated?* We also provide respondents with an example illustrating the calculation of the automatable share of core tasks, accessible by clicking an icon on the screen. In addition, we elicit respondents' confidence in their beliefs on a seven-point Likert scale.

Second, after providing information to the treatment group, we elicit all respondents' beliefs about the share of automatable core tasks that they perform themselves in their jobs: *What percentage of the core activities you specifically perform in your job do you think can be automated?* We intentionally worded this question differently from the preceding belief-related question to minimize the risk of confusing respondents by asking the exact same question twice, which could potentially bias their responses. By eliciting beliefs about the automatability of both their occupation on average and their own job, we can identify (i) the extent to which respondents are misinformed about the occupation-level data provided in the treatment, and (ii) how correcting these perceptions affects their beliefs about personal automation risk, which ultimately influences their labor-market concerns and willingness to train.[12]

3.3.3. Eliciting Labor-Market and Further-Training Outcomes

Our main outcomes are (i) respondents' labor-market expectations, (ii) respondents' stated likelihood that they will participate in further training and retraining, and (iii) the fraction of wages that respondents are willing to forgo to participate in further training.

First, we elicit respondents' labor-market expectations by asking to what extent they agree with a number of statements regarding their professional future. The nine statements are grouped into two domains: the first measures whether respondents are concerned about their professional future and about being replaced by computers or machines (*labor-market concerns*). The second measures whether respondents expect changes in their work environment in the future, such as changes in the task they perform or the hours they work (*work-environment change*). In particular, respondents stated their agreement to the following statements on a five-point Likert scale: *1) I am concerned about my professional future. 2) I*

[12] Note that beliefs regarding the average automatability within an occupation might not align with beliefs about the automatability of a respondent's specific job, since task profiles within a given occupation could vary widely across individual jobs. Furthermore, respondents have unique insights into the particular tasks they undertake in their current role, which may produce differences in their automatability beliefs about their jobs compared to their occupations' average.

will have different tasks in my job in the future than I have now. 3) I have a low risk of becoming unemployed. 4) I am concerned that new technologies will replace many tasks in my job. 5) I believe that my job will no longer exist in a few years. 6) I expect to be paid a higher wage in the future. 7) I will work on more demanding tasks in the future. 8) I will work fewer hours in the future than I do now because computers and computer-controlled machines will replace some of my activities. 9) I will work a lot with computers or computer-controlled machines in the future. We combine items by domain into two indices which are standardized to mean zero and standard deviation one. The index *labor-market concerns* (*work-environment change*) combines statements 1, 3-6 (statements 2, 7-9), with higher values reflecting greater concerns (greater expected changes).[13]

Second, we gauge respondents' likelihood of engaging in further training (courses designed to enhance skills, typically for their current job) and retraining (courses intended for transitioning to another occupation) within the next two years, on a scale ranging from zero to 100 percent. Further training courses are very heterogeneous in intensity. For the purpose of our study, we follow funding eligibility criteria from the Federal Employment Agency and focus on courses entailing at least 120 hours of training (see section 3.1 for details on the institutional background). In the retraining question, we define it as a program where respondents gain skills for a new occupation, as opposed to enhancing skills for their current job. Besides assessing the likelihood of enrolling in a retraining program, we also inquire which occupation respondents would choose for retraining if they were to do so within the next two years.

Third, to elicit respondents' willingness to pay for further training, we ask them about the fraction of their wages that they would be willing to forgo while completing further training of at least 120 hours outside their company. To answer this question, respondents can indicate a number from zero to 100, where zero indicates that respondents would not be willing to forgo any part of their current wage.

3.4. The Econometric Model

We estimate the effect of the information treatment on outcomes with the following regression model:

$$y_i = \alpha_0 + \alpha_1 Information_i + \delta' X_i + \varepsilon_i \quad (1)$$

[13] Combining the nine items into two indices can alleviate concerns of multiple hypothesis testing and improve statistical power (Anderson 2008; Heller et al. 2017).

where y_i is the outcome variable of interest for respondent i, e.g., labor-market expectations or likelihood of participating in further training. $Information_i$ indicates whether respondent i was in the information-treatment group, or the control group. X_i is a vector of control variables, and ε_i is the error term. Since ε_i is uncorrelated with treatment status through randomization, the coefficient α_1 provides an unbiased estimate for the causal treatment effect of information provision even without adding further control variables. As the inclusion of control variables can increase the precision of estimates, we show results with control variables in our analyses.[14]

As previously discussed and supported by existing research, individuals in occupations with high automatability are strongly underrepresented in continued education and further training initiatives (Heß et al. 2019; OECD 2021), despite the fact that they would benefit most from further training. Consequently, examining how information provision influences various worker subgroups categorized by their occupations' automatability is particularly interesting from a distributional viewpoint. Therefore, we estimate a second model which includes an interaction term of the treatment indicator and a dummy variable Low Automation_i, coded one if the automatability of a respondent's occupation is less than 50 percent:[15]

$$y_i = \alpha_0 + \alpha_1 \text{Information}_i + \alpha_3 \text{Low Automation}_i + \alpha_4 \text{Information}_i \times \text{Low Automation}_i + \delta' X_i + \varepsilon_i \qquad (2)$$

We correct for multiple hypothesis testing for our pre-registered primary outcomes, applying the correction proposed by List et al. (2019), which is based on Romano and Wolf (2010). Overall, correcting for multiple outcomes does not change the interpretation of our results. We report corrected p-values in the table notes of Tables 2, 3, and 4.

3.5. Sample Balance and Descriptive Statistics

We perform a balancing test to check whether the randomization worked as intended, i.e., whether respondents' observable characteristics are balanced between treatment and control group (see Appendix Table A1). Reassuringly, only two out of 28 pairwise comparisons are

[14] All qualitative results hold without including control variables (available on request).

[15] We would expect the size of the treatment effects to also correlate with the absolute distance between respondents' prior beliefs and the information treatment. In our sample, we do not have enough power to detect these effects although results show the expected pattern (results available on request).

statistically significant at the five percent level. In addition, item non-response is not correlated with treatment status (see Appendix Table A2).[16]

Respondents in our sample work in 1,118 different occupations. The most common occupations are "Management Assistant - Office Management", "Office Clerk" and "Bank Clerk". This corresponds well to administrative data from the Federal Employment Agency demonstrating that most respondents in Germany work in the occupational group "office and secretariat" (Statistik der Bundesagentur für Arbeit 2023b). The average automatability across all occupations in our sample is 51.3 percent. Occupations with the highest automatability (100 percent) are, for example, "Administrative employee" and "Machine, plant, and container cleaner". Occupations with the lowest automatability (zero percent) are occupations such as "Social Worker / Social Pedagogue" and "Care Worker / Everyday Companion".

We also match respondents' reported occupations to additional data on the typical requirement level and the occupational field using the German Classification of Occupations from 2010 (Paulus and Matthes 2013). This classification divides occupations into four requirement-level categories, distinguishing between unskilled or semi-skilled activities, specialist activities, complex specialist activities, and highly complex activities. We compare the distribution of requirement levels in our sample with administrative data from the Federal Employment Agency (Statistik der Bundesagentur für Arbeit 2023a). As it turns out, most respondents in our sample (in administrative data), 52.3 percent (57.3 percent), work in specialist activities, and only 6.1 percent (15.7 percent) in unskilled or semi-skilled activities. 22.9 percent (13.1 percent) work in complex specialist activities, while 18.7 percent (13.8 percent) work in highly complex activities. Consequently, our data exhibits a slight overrepresentation of respondents engaged in complex and highly complex tasks, compared to those in unskilled, semi-skilled, or specialist roles. Given that lower-skilled occupations often have higher automatability, our results may present lower-bound estimates of the information effects for the general population.

In terms of occupational fields, our sample encompasses all major occupations of the German population (see Appendix Table A3). The majority of respondents works in administration and organization occupations (24.2 percent), whereas the smallest proportion works in agriculture (1.6 percent). Compared to the German population, workers in production

[16] In our preferred specification, we do not constrain respondents to having valid answers for all items of the survey. Due to item non-response, this means that observation numbers vary slightly across different specifications. Results remain virtually unchanged if we restrict the sample to respondents who answered all questions. Details available upon request.

and manufacturing are underrepresented in our sample (14.2 percent vs. 20.7 percent in the population). By contrast, workers in commercial services are slightly overrepresented in our sample (16.4 percent vs. 11.4 percent). Overall, our sample, designed to represent the German adult population, accurately mirrors occupation types, fields, and skill levels of workers in Germany.

4. Results

We first present descriptive evidence on respondents' prior beliefs (section 4.1.1) and correlations between prior beliefs, the occupations' actual automatability, and respondents' likelihood of participating in further training (section 4.1.2). Section 4.2 presents our experimental results. Section 4.3 presents descriptive evidence on the reasons for (not) participating in further training.

4.1. Descriptive Results

4.1.1. Are Respondents Aware of Their Occupations' Automatability?

First, we examine whether respondents are aware of their occupations' automatability. Figure 1 shows the distribution of the actual automatability of our respondents' occupations based on data from the "IAB-Job-Futuromat" (transparent bars), and respondents' prior beliefs about their occupations' automatability (blue bars). Occupations' automatability is distributed fairly evenly from zero to 100 percent, while respondents' beliefs are skewed towards lower automatability.

In Figure 2, we plot respondents' beliefs against the actual automatability of their occupations. Those positioned on the 45-degree line have beliefs that correspond with their occupations' actual automatability. Respondents below (above) the 45-degree line underestimate (overestimate) their occupations' automatability. A majority of 67.5 percent of respondents underestimate their automatability, while 21.4 percent overestimate it. Only 11.1 percent are within the accuracy range (i.e., within a five-percentage point deviation above or below the 45-degree line).[17] The correlation between respondents' beliefs and their

[17] Note that rounding is an important concern in the elicitation of continuous beliefs in surveys (Manski and Molinari 2010). We can assess the prevalence of rounding in our context by identifying respondents' rounding behavior throughout the questionnaire. In total, we use four questions in the experiment where respondents indicate continuous answers between zero and 100 with a slider. Only nine percent of respondents indicate a number which is a multiple of ten for each of the four sliders. This suggests that rounding is not a major concern in our study.

occupations' automatability is statistically significantly positive but very small at 0.2 (Figure 2). This implies that respondents in occupations with high automatability have the largest misperceptions of their automatability. Appendix Figure A3 emphasizes that this is driven by differences in automatability, not differences in beliefs: both groups of respondents (with high and low automatability) indicate similar beliefs about their occupations' automatability. Comparing the medians of beliefs and actual automatability, the difference is only approximately 5 percentage points for respondents with low automatability (20.0 vs. 25.0 percent) while it is large at 45 percentage points for respondents with high automatability (30.0 vs. 75.0 percent).

Overall, we document sizeable underestimation of automatability. This is in line with the literature documenting favorable misperceptions in other labor-market beliefs, for example, optimistic bias in job seekers' beliefs about their job-finding probability (Mueller et al. 2021) or underestimation of earnings at another potential employer (Jäger et al. 2021). However, on average, respondents in occupations with higher automatability are significantly less confident about their answer (mean values 4.6 vs. 4.3 on a seven-point scale).

4.1.2. Which Respondents Are Willing to Participate in Further Training?

In this section, we explore whether the willingness to participate in further training and retraining correlates with the automatability of respondents' occupations or their beliefs.

In the control group, respondents state an average likelihood that they will participate in further training (retraining) of 40.7 percent (27.1 percent). The willingness to participate in further training declines slightly with increasing automatability of respondents' occupations. Respondents in occupations with an automatability of below 50 percent state on average a 44.1 percent likelihood of participating in further training, which is 6.5 percentage points higher compared to respondents in high-automatability occupations.[18] Regarding retraining, respondents in occupations with low automatability state a 28.8 percent likelihood of participating on average, while respondents with high automatability state a likelihood of 25.6 percent ($p < 0.05$). This corroborates that the lower participation in further training for

[18] This pattern is also reflected in respondents' previous participation in further training. Respondents with high automatability of their occupation participated in fewer further-training measures in the past than those with low automatability (Appendix Figure A4). Furthermore, respondents in high-automatability occupations who did not previously participate in any training state the lowest likelihood of participating in the future (32.1 percent) compared to those who previously participated (43.3 percent). Respondents in low-automatability occupations without (with) previous training participation state a 34.8 (47.6) percent likelihood of future training participating. These two differences in future training participation by past training participation are statistically significant.

respondents with a high share of routine and automatable core tasks documented in the literature already emerges in stated participation expectations (Heß et al. 2019).

As documented in section 4.1.1., a large proportion of respondents underestimates their occupations' automatability. It seems likely that individual training decisions are based on respondents' beliefs about automatability. As Figure 3 shows, the stated likelihood of participating in further training increases significantly with increasing beliefs about automatability up to an automatability level of 50 percent and declines for higher levels.[19] For retraining, we find a statistically significant and positive relationship throughout: the higher the beliefs about the occupations' automatability, the higher the stated likelihood of participating in retraining. Thus, respondents seem to perceive further training as especially useful if their occupations' susceptibility to automation is moderate, while retraining becomes more attractive with increasing beliefs about automatability.

While these analyses are purely descriptive, we next present the results from our experiment, which allows us to test whether providing information about occupations' automatability causally affects respondents' willingness to train.

4.2. Experimental Results

4.2.1. Beliefs About Own Job's Automatability

We first examine whether information about the automatability of respondents' occupations affects their beliefs about the automatability of their current job. To this end, we estimate treatment effects of information provision on respondents' beliefs about the share of automatable tasks that they perform in their job.

Table 1 shows that the treatment increases respondents' beliefs about the automatability of their own job. Since respondents, on average, underestimate the share of automatable tasks in their occupation (see section 4.1.1), this implies that respondents update their beliefs in line with the information provided. On average, respondents in the control group believe that 26.8 percent of core tasks in their current jobs are automatable (see baseline mean in column 1), which is significantly below the actual average automatability for their occupations (52.1 percent). The treatment increases beliefs among all respondents by 5.1 percentage points. Column 3 reports treatment effects on the difference between the actual automatability of

[19] Figure 3 plots the unconditional relationships between respondents' beliefs and their stated likelihood of participating in further training (dark green) and retraining (light green). The results remain similar when controlling for age and gender.

respondents' occupations and their beliefs about their own job's automatability. While control-group beliefs about the automatability of their own job are 25.3 percentage points below the actual automatability of their occupations, the treatment reduces this gap by 7.0 percentage points.

Appendix Figure A5 shows the correlation between respondents' beliefs about their own jobs' automatability and their occupations' automatability, separately for control and treatment group. In the control group, beliefs about their own jobs' automatability are largely flat across the whole spectrum of actual automatability. In the treatment group, respondents' beliefs increase with actual automatability.

The overall information-treatment effect on automatability beliefs is largely driven by respondents in high-automatability occupations. Based on equation (2), the regressions in columns 2 and 4 of Table 1 report treatment effects separately for respondents in occupations with high and low automatability. In the control group, respondents in high-automatability occupations – defined as occupations with an automatability of 50 percent and more - believe on average that their own job's automatability is 30.3 percent, only 7.3 percentage points higher than control-group beliefs of respondents in occupations with low automatability. The treatment increases beliefs among those in high-automatability occupations significantly by 12.9 percentage points, and slightly decreases beliefs among those in low-automatability occupations by 2.4 percentage points (column 2). The treatment effect for respondents in high-automatability occupations corresponds to a 13.9 percentage-points reduction in the difference between their occupations' actual automatability and their beliefs about their jobs' automatability (column 4). Thus, the information treatment significantly corrects these respondents' beliefs on their own jobs' automatability upwards.

4.2.2. Labor-Market Expectations

Next, we show that information about occupations' automatability increases respondents' labor-market concerns and affects their expectations about future changes in their work environment. Table 2 presents estimations based on equation (1) in columns 1 and 3, and equation (2) in columns 2 and 4, with the two indices of *labor-market concerns* and *work-environment change* as dependent variables.

On average, the information treatment significantly increases the index of *labor-market concerns* by 9.7 percent of a standard deviation. This overall effect is primarily driven by respondents in occupations with high automatability (column 2): the treatment effect for this group is 15.9 percent of a standard deviation, while the treatment effect for those in occupations with low automatability is small and statistically insignificant.

Treated respondents are also more likely to expect changes in their future work environment. The treatment increases the index *work-environment change* by 13.0 percent of a standard deviation. Again, the treatment effect is larger for respondents in high-automatability occupations than low-automatability occupations (16.0 versus 10.5 percent of a standard deviation), although the difference between groups is not statistically significant (column 4).

As detailed in the table note, average treatment effects, and treatment effects for respondents in high-automatability occupations remain statistically significant when correcting for multiple hypothesis testing. The interaction terms are no longer statistically significant.

Appendix Table A4 demonstrates that the treatment effects on the indices are due to impacts on various components of these indices.[20] The treatment effect on the *labor-market concerns* index of high-automatability respondents is mainly driven by increased concerns that new technologies will replace many tasks in their job (column 3), and that their job will no longer exist in a few years (column 4). The effect on the *work-environment change* index is driven by all index components, but beliefs that respondents will work on more demanding tasks in the future, which is not affected by the treatment. Thus, respondents have a nuanced interpretation of the information on automatability, incorporating both labor-displacing and labor-reinforcing narratives of technological change.

4.2.3. Participation in Further Training and Retraining

We now show that providing information about occupations' automatability also increases respondents' willingness to participate in further training and retraining. In the control group, respondents state a 40.7 percent likelihood of participating in further training on average, and a 27.1 percent likelihood of retraining (Table 3). The information treatment significantly increases the likelihood of participation in further training (retraining) by 2.3 percentage points (3.4 percentage points). These effects correspond to 5.8 and 12.5 percent of the mean, respectively. Appendix Figure A6 reports the distribution of reported likelihoods of participation for the control group (blue bars) and the treatment group (transparent bars). For further training (Panel (a)), the information treatment tends to reduce the share of respondents who report a probability of participation close to zero. For retraining (Panel (b)), the share

[20] Moreover, the table shows that only minorities of respondents in the control group are concerned about their professional future, whereas majorities expect to work on more demanding tasks, and work a lot with computers in the future (see bottom of the table).

reporting a zero probability to participate is much lower, and the share reporting a 100 percent probability to participate is much higher. The treatment significantly increases the latter share.

The information-treatment effect on the likelihood to participate in further training and retraining is more pronounced among respondents in high-automatability occupations: the treatment significantly increases their likelihood to participate in further training and retraining by 4.6 and 5.2 percentage points, respectively (see Table 3, columns 2 and 4). The treatment effect for respondents in occupations with low automatability is significantly smaller, and not statistically significant for either outcome.[21] As discussed in section 4.1.2, willingness to participate in further training and retraining is lower among respondents in high-automatability occupations. The information treatment closes these gaps (almost) entirely.

Consistent with the results on stated likelihood to participate in training, we also find significant treatment effects on respondents' willingness to accept a reduced wage while participating in further training. Table 4 shows that the information treatment significantly increases the fraction of wages respondents are willing to forgo by 1.3 percentage points, or 13.1 percent compared to the control-group mean of 9.6 percent (column 1). Again, this effect is driven by those in occupations with high automatability, for whom the effect is highly statistically significant at 2.6 percentage points (column 2). In addition, the treatment marginally significantly increases their probability to forgo any positive share of their wages (column 4).[22]

4.2.4. Further Outcomes

Occupation Choice.[23] We also ask respondents which occupations they would choose for retraining if they were to retrain in the next two years. On average, respondents in the treatment group report retraining occupations with a slightly higher automatability, although this effect is not statistically significant (see Table 5, column 1). One possible explanation for this small effect is that respondents remain uninformed about the automatability of other occupations, even though they receive automatability information about their current occupation. Given the large misperceptions of respondents' own occupation documented in section 4.1.1, it is

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[21] The average treatment effects, and the treatment effects for respondents in high-automatability occupations, remain statistically significant when correcting for multiple hypothesis testing. The interaction terms lose their statistical significance (see notes of Table 3).

[22] The average treatment effect as well as the treatment effect for high-automatability respondents remain statistically significant when correcting for multiple hypothesis testing. The effects on the share of those willing to forgo any positive share of their wage become insignificant (see notes of Table 4).

[23] While we pre-registered the question on which retraining occupations respondents would choose, analyses in this section were not pre-registered and are explorative.

plausible that respondents are also unaware of the automatability of other occupations. We also find no statistically significant effect among respondents in high-automatability occupations.

Furthermore, we also find no significant treatment effects on whether respondents want to retrain to (i) another occupational field, (ii) another occupational field with low automatability, or (iii) an occupation with higher requirements than their current occupation (see columns 3-8). However, treated respondents in high-automatability occupations are marginally significantly more likely to retrain to occupations with lower wages (column 10).

Taken together, this analysis suggests that even though treated respondents are more willing to retrain, they do not plan to switch to occupations with lower automatability or higher wages. One interpretation of this finding is that respondents are generally not aware of key characteristics of their occupational outside options (e.g., Jäger et al. 2021).

Policy Views. In this section, we explore how information about occupations' automatability affects respondents' views on public policies related to increase take-up of further training.

First, respondents were asked whether they favor or oppose the policy proposal to make training participation compulsory for persons whose occupation is affected by structural change and digitalization. While 62.5 percent in the control group (rather or strongly) support this proposal, the information treatment does affect these preferences (see Appendix Table A5, columns 1 and 2). We also ask respondents whether they believe that participation in further training is a good strategy to cope with structural change. Three-quarters of respondents (76.7 percent) in the control group agree with this statement, but again the information treatment does not affect this belief (see Appendix Table A5, columns 3 and 4).

Similarly, treated respondents are not more likely to think that the need for further training for (1) all employees in Germany or (2) employees in the same occupation as themselves will increase.[24] In the control group, 66.2 percent (50.4 percent) believe that the need for further training for all employees (employees in the same occupation) will "strongly" or "rather" increase (see Appendix Table A5, columns 5 and 7). Hence, respondents perceive a greater need for further training among those in other occupations than their own, which could be due to optimistic biases previously documented for other labor-market decisions (e.g., Mueller et al. 2021).[25]

[24] Questions are worded as follows: *What do you think, will the need for further training for the following groups of people increase, decrease, or remain unchanged in the future? (1) For all employees in Germany (2) For people who are in the same occupation as me.*

[25] Interestingly, this pattern is consistent with the observation that 53.8 percent of Germans think that there are more losers than winners because of structural change, while only 26.6 percent see themselves as a loser of structural change Werner et al. 2022.

Overall, these results show that respondents have a positive view about further training as a means to keep pace with structural change, and support according policy proposals. Despite its effects on respondents' labor-market concerns, the treatment does not affect respondents' policy views, which is a pattern in line with previous research on other policy domains (e.g., Alesina et al. 2018; Kuziemko et al. 2015; Haaland and Roth 2023).

4.3. Reasons for (Non-)Participation

Finally, we ask all respondents about their reasons for (not) wanting to participate in further training. Respondents are asked to what extent they agree with a set of statements relating to financial, time, and employer constraints. Previous literature has identified these as potential barriers to participating in further training (see, e.g., van den Berg et al. 2019, Müller and Wenzelmann 2020, Osiander and Stephan 2020). As shown in Appendix Table A6, almost half of the respondents state that they face financial and employer constraints (45.4 and 45.0 percent, respectively), 35.2 percent face time constraints, and 39.5 percent do not want to participate in measures offered by the Federal Employment Agency. As expected, providing information about automatability does not affect agreement with resource and personal constraints, as these factors are unaffected by the provided information.[26]

In contrast, respondents' do not seem to feel uninformed about further training possibilities and finance options. Upon being offered extra information at the end of the survey, merely 38.6 percent of respondents choose to access it. The information treatment does not affect information-acquisition behavior (see Appendix Table A8).[27]

Finally, we examine whether training participation depends on respondents' age and educational attainment.[28] One might expect that workers closer to their retirement age are less willing to participate in further training, and react less strongly to the information provided (e.g., Innocenti and Golin 2022). In fact, Table 6 shows that information-treatment effects on willingness to (re)train are confined to respondents below age 60, whereas effects for those above 60 years are small and statistically insignificant (columns 1 and2). A likely reason is that younger workers, with more time before retirement, see greater potential for technological

[26] Similarly, we find no information effects on other possible barriers to training, like insecurity about the returns to training, perceived necessity of further training, or confidence about professional future (see Appendix Table A7).

[27] We ask respondents the following question: *Would you like to receive more information about further training opportunities, funding, and providers in Germany?*

[28] This heterogeneity analysis was not pre-registered and should therefore be viewed as exploratory.

transformation impacting their careers and for recouping the benefits of new skills, unlike older workers who are closer to Germany's retirement age of 67.

Turning to educational attainment, columns 3 and 4 of Table 6 reveal that the information treatment only increases willingness to (re)train among the lower educated (i.e., without university entrance qualification), whereas the higher educated do not react to the treatment. This result is in line with our main finding that information effects are stronger among respondents in high-automatability occupations, reflecting the negative correlation between respondents' educational attainment and automatability.

5. Conclusion

Technological and structural change in the labor market are increasing the demand for new skills in the workforce. Further training and retraining therefore emerge as key elements to bridge the gap between workers' initial education and current developments in skill demand. Yet, participation rates in training programs are especially low for individuals in occupations with high automation risk. We show that one potential reason for the lack of training participation in this vulnerable group of workers are misperceptions regarding the automatability of tasks commonly performed in their occupations. On average, respondents underestimate the automatability of their occupation, especially those in occupations with high automatability. Providing information about the automatability of workers' occupations increases different dimensions of their labor-market concerns, and their beliefs that their work environment will change in the future towards othertasks. Respondents exhibit a nuanced understanding of the provided information regarding automatability, encompassing both labor-displacing and labor-reinforcing narratives of technological change. Importantly, the provided information increases willingness to participate in further training and retraining, and the fraction of wages that respondents are willing to forgo to participate in further training. Treatment effects are larger for respondents in occupations with high automatability, who have the highest risk of experiencing adverse impacts of technological transformation. Thus, providing information about occupations' automatability can reduce inequality in training participation between workers in high- and low-automatability occupations. For future research, it would be interesting to investigate whether the increased willingness to train actually results in increased training participation.

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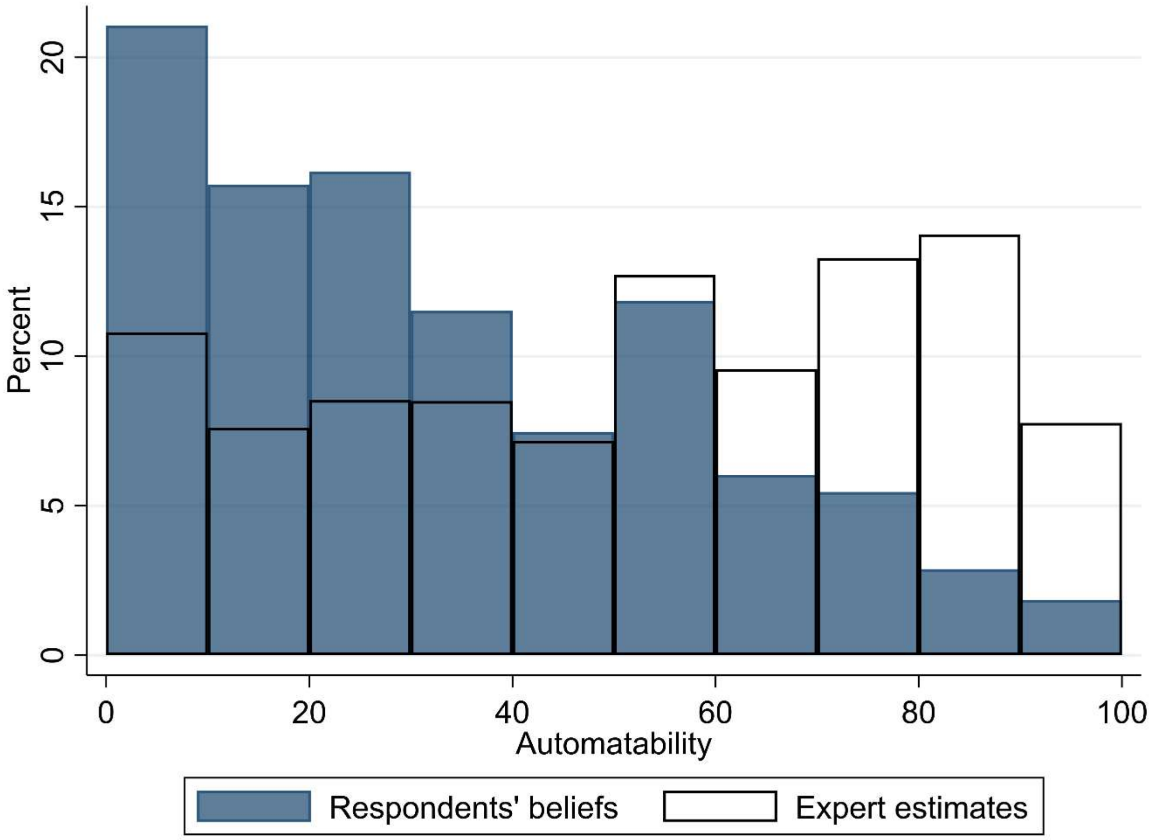
Figures and Tables

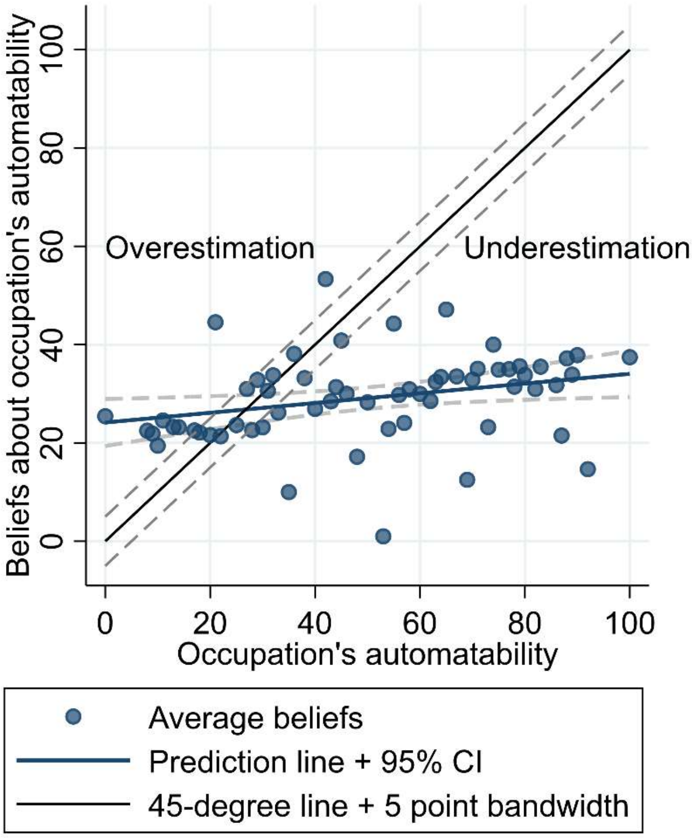
Figures

Figure 1: Distribution of respondents' beliefs and automatability of respondents' occupations



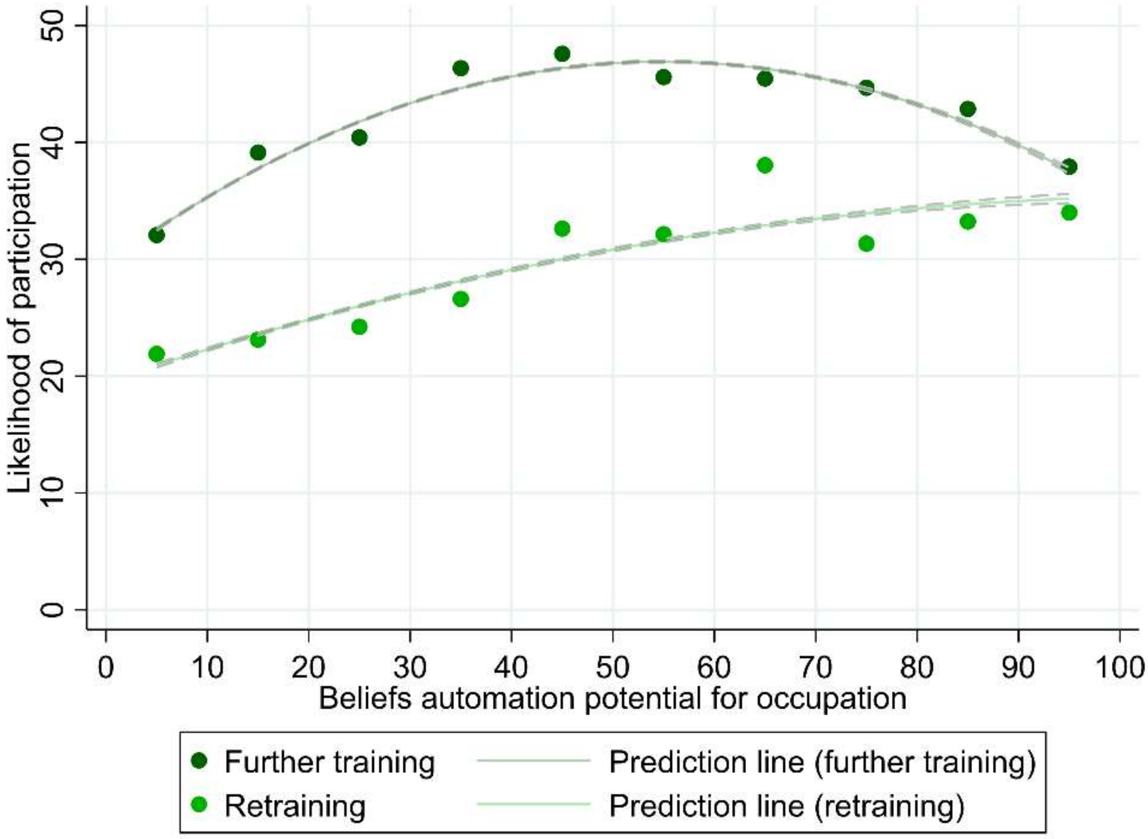
Notes: Blue bars depict bins for respondents' answers to the question "*What do you think is the percentage of core activities that people perform in the profession [answer from earlier question about current occupation] that can be automated?*". Transparent bars depict bins for the automatability of respondents' occupations according to expert estimates by the Research Institute of the Federal Employment Agency in Germany (IAB). Data source: ifo Education Survey 2022.

Figure 2: Difference between respondents' beliefs and occupations' automatability



Notes: Respondents' answers to the question "*What do you think is the percentage of core activities that people perform in the profession [answer from earlier question about current occupation] that can be automated?*" are depicted as averages for each occupation's automatability (calculated by experts from the IAB). The blue line depicts the prediction line and the 95 percent confidence interval. The black line depicts the 45-degree line with a 5-point bandwidth. Points above the 45-degree line indicate an overestimation of the occupation's automatability and points below indicate an underestimation. Data source: ifo Education Survey 2022.

Figure 3: Beliefs about automatability and likelihood of participating in further training and retraining



Notes: Respondents' answers to the questions "*How likely is it that you yourself will participate in further training of at least 120 hours within the next two years?"* and *"How likely is it that within the next two years you will complete retraining to another occupation?*" are depicted as averages for 10 bins of respondents' beliefs about their occupations' automatability. The dark green dots depict the averages for the likelihood to participate in further training, and the light green dots depict the ones for retraining. Data source: ifo Education Survey 2022.

Tables

Table 1: Effect of information treatment on beliefs

	Beliefs about own job's automatability		Difference occupation's automatability and beliefs about own job's automatability	
	(1)	(2)	(3)	(4)
Information	5.124***	12.874***	-6.989***	-13.858***
	(0.879)	(1.260)	(1.123)	(1.336)
Low Automation		-7.299***		-43.694***
		(1.192)		(1.333)
Information x Low Automation		-15.321***		14.958***
		(1.646)		(1.801)
Covariates	Yes	Yes	Yes	Yes
Baseline mean	26.822	30.290	25.290	46.857
Observations	3005	3005	3005	3005
R-squared	0.056	0.168	0.063	0.394
Information Effect for Low Automation		-2.447**		1.100
		(1.065)		(1.213)

Notes: OLS regressions. Dependent variables: (1) – (2) Beliefs about own job's automatability; (3) – (4) Occupation's actual automatability minus beliefs about own job's automatability; Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. Covariates include: Age, female, born in Germany, West Germany, living in large city, risk, patience, parents with university education, income, current employment status, middle school degree, high school degree, partner living in household, parental status, and imputation dummies. Outcomes in this table are pre-registered as secondary outcomes. Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Information effect on labor-market expectations (index)

	Index labor-market concerns		Index work-environment change	
	(1)	(2)	(3)	(4)
Information	0.097***	0.159***	0.130***	0.160***
	(0.036)	(0.049)	(0.034)	(0.046)
Low Automation		-0.194***		-0.129***
		(0.049)		(0.048)
Information x Low Automation		-0.118*		-0.055
		(0.071)		(0.067)
Covariates	Yes	Yes	Yes	Yes
Baseline Mean	0.000	0.084	0.000	0.036
Observations	3011	3011	3011	3011
R-squared	0.088	0.103	0.148	0.155
Information Effect for Low Automation		0.041		0.105**
		(0.050)		(0.049)

Notes: OLS regressions. Dependent variables: (1) – (2) Index labor-market concerns; (3) – (4) Index work-environment change; Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. See Table 1 for included covariates. Outcomes in this table are pre-registered as primary outcomes. MHT corrected p-values: for Information: 0.032 in column (1), 0.015 in column (2), 0.001 in column (3), 0.001 in column (4). For Information x Low Automation: 0.159 in column (2), 0.414 in column (4). Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Information effect on likelihood to participate in further training and retraining

	Likelihood further training		Likelihood retraining	
	(1)	(2)	(3)	(4)
Information	2.343**	4.647***	3.401***	5.194***
	(1.063)	(1.465)	(0.999)	(1.389)
Low Automation		4.977***		1.860
		(1.498)		(1.359)
Information x Low Automation		-4.755**		-3.658*
		(2.132)		(2.007)
Covariates	Yes	Yes	Yes	Yes
Baseline Mean	40.740	37.576	27.111	25.555
Observations	2973	2973	2928	2928
R-squared	0.142	0.145	0.188	0.189
Information Effect for Low Automation		-0.108		1.535
		(1.541)		(1.441)

Notes: OLS regressions. Dependent variables: (1) – (2) Stated likelihood to participate in further training (between zero to 100); (3) – (4) Stated likelihood to participate in retraining (between zero to 100); Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. See Table 1 for included covariates. Outcomes in this table are pre-registered as primary outcomes. MHT corrected p-values: for Information: 0.051 in column (1), 0.001 in column (2), 0.001 in column (3), 0.001 in column (4). For Information x Low Automation: 0.120 in column (2), 0.178 in column (4). Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Information effect on willingness to forgo wage for training

	Willingness to forgo wage		**Willingness to forgo wage > 0**	
	(1)	(2)	(3)	(4)
Information	1.250**	2.612***	0.014	0.048*
	(0.613)	(0.871)	(0.017)	(0.024)
Low Automation		0.354		0.026
		(0.841)		(0.025)
Information x Low Automation		-2.736**		-0.068*
		(1.225)		(0.035)
Covariates	Yes	Yes	Yes	Yes
Baseline Mean	9.558	8.999	0.476	0.449
Observations	3008	3008	3008	3008
R-squared	0.103	0.105	0.106	0.107
Information Effect for Low Automation		-0.124		-0.020
		(0.864)		(0.025)

Notes: OLS regressions. Dependent variables: (1) – (2) Share of wage willing to forgo (zero to 100); (3) – (4) Dummy variable coded one if stated willingness is non-zero (positive); Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. See Table 1 for included covariates. Outcomes in this table are pre-registered as primary outcomes. MHT corrected p-values: for Information: 0.079 in column (1), 0.010 in column (2), 0.397 in column (3), 0.208 in column (4). For Information x Low Automation: 0.137 in column (2), 0.220 in column (4). Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Characteristics of retraining occupations

	Automatability		Other occupational field		Low automation occupational field		Higher requirement level		Mean wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Information	1.217	1.686	0.010	-0.028	-0.015	-0.035	-0.008	-0.031	-68.423	-117.155*
	(1.237)	(1.736)	(0.019)	(0.027)	(0.018)	(0.024)	(0.019)	(0.028)	(48.633)	(67.486)
Low Automation		-9.578***		-0.089***		0.101***		-0.163***		-123.730*
		(1.728)		(0.028)		(0.026)		(0.027)		(68.479)
Information x Low Automation		-1.099		0.077**		0.040		0.046		98.639
		(2.440)		(0.039)		(0.037)		(0.038)		(97.380)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	44.024	49.308	0.638	0.684	0.318	0.263	0.348	0.429	3889.858	3897.594
Observations	2326	2326	2449	2449	2449	2449	2447	2447	2190	2190
R-squared	0.027	0.054	0.010	0.014	0.049	0.066	0.017	0.039	0.146	0.147
Information Effect for Low Automation		0.587		0.049*		0.005		0.015		-18.517
		(1.711)		(0.028)		(0.027)		(0.026)		(70.552)

Notes: OLS regressions. Dependent variables: (1) – (2): Automatability of the indicated retraining occupation (zero to 100); (3) – (4): Dummy variable indicating whether the retraining occupation is in a low automation occupational field (health & social services, social science and agriculture); (5) – (6): Dummy variable indicating whether the retraining occupation is in another occupational field; (7) – (8): Dummy variable indicating whether the retraining occupation is of a higher requirement level; (9) – (10): Mean wage of the retraining occupation. Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. See Table 1 for included covariates. Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 6: Heterogeneity of information treatment effects across subgroups

	Subgroup: Age above 60		Subgroup: University Entrance Qualification	
	Likelihood further training	**Likelihood retraining**	**Likelihood further training**	**Likelihood retraining**
	(1)	(2)	(3)	(4)
Information [baseline: not in subgroup]	2.575**	3.683***	4.375***	4.667***
	(1.113)	(1.072)	(1.422)	(1.307)
Subgroup	-4.238	-4.838**	5.246***	-1.802
	(2.812)	(2.027)	(1.910)	(1.735)
Information x Subgroup	-2.732	-3.378	-4.734**	-2.955
	(3.698)	(2.578)	(2.139)	(2.026)
Covariates	Yes	Yes	Yes	Yes
Baseline Mean	42.288	28.932	35.349	24.548
Observations	2973	2928	2970	2925
R-squared	0.144	0.191	0.143	0.188
Information Effect for Subgroup	-0.157	0.305	-0.359	1.712
	(3.524)	(2.347)	(1.597)	(1.550)

Notes: OLS regressions. Dependent variables: (1) Stated likelihood to participate in further training (zero to 100); (2) Stated likelihood to participate in retraining (zero to 100); (3) Stated likelihood to participate in further training (zero to 100); (4) Stated likelihood to participate in retraining (zero to 100); Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. See Table 1 for included covariates. Heterogeneities in this table are pre-registered. Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Appendix A: Institutional Background

This section provides an overview of the further training system in Germany. The system is characterized by a high degree of decentralization due to Germany's federal structure.

There are five types of learning provision: Basic Continuing Education and Training (CET), General CET, Vocational CET, CET in Higher Education and Adult Liberal Education (OECD 2021). Basic CET refers to non-formal learning opportunities for adults lacking basic skills. General CET includes formal education opportunities for adults to obtain school leaving certificates. Vocational CET encompasses formal and non-formal learning opportunities covering different levels, ranging from basic vocational qualifications to Master crafts people, Bachelor's degrees and certified business economists (OECD 2021). It also includes vocational retraining, adjustment training and vocational upskilling. CET in Higher Education includes Bachelor's and Master's degree programs, while Adult Liberal Education comprises learning opportunities offered by Adult Education Centers.

In addition, there are several types of further training: In-company training, individual job-related, and non-job-related. In-company training is the most common type. The average duration for in-company further training is 29 hours, individual job-related approx. 153 hours, and non-job-related further training is 56 hours (BMBF 2018).

Overall, there are approximately 18,000 public and private further training providers (Bundesinstitut für Berufsbildung 2020), including public institutions such as vocational schools or higher education institutions, CET institutions operated by enterprises, or groups of enterprises, social and economic partners such as trade unions and employer organizations, Chambers of Commerce and Trade, Chambers of Skilled Crafts, CET institutions run by churches, political parties, trade unions, foundations, other associations and Adult Education Centers.

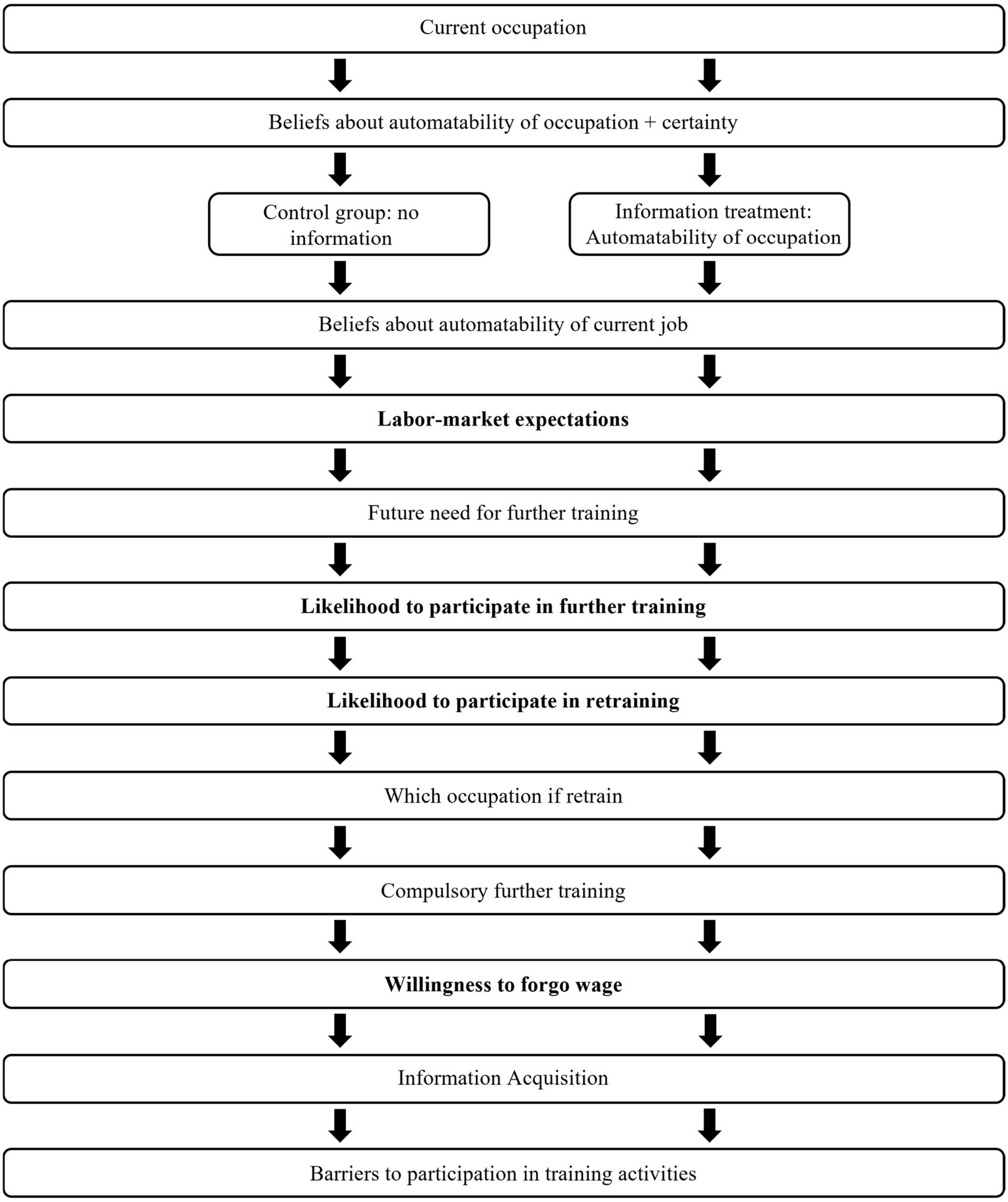
The further training system in Germany is subject to various levels of regulation and is governed by numerous legal bases. These include collective bargaining agreements and company agreements, laws, and regulations at the state level. Companies, employees, and the public sector share the responsibility and obligation for further vocational training and its funding.

According to the IW Continuing Education Survey 2020, the participation rate in further education by German companies was approximately 88 percent in the year 2019. Furthermore, the ifo Education Survey reported that 63 percent of respondents stated that they had participated in further training in the past. Conversely, this means that more than one third (37 percent) have not yet participated in any further training (Werner et al. 2022).

Furthermore, the German government provides support for further education through assistance and funding programs. For example, the Federal Employment Agency offers financial support to job seekers who wish to participate in further training measures to enhance their employability. Additionally, there are various government educational grants and tax benefits available to companies that invest in the further education of their employees.

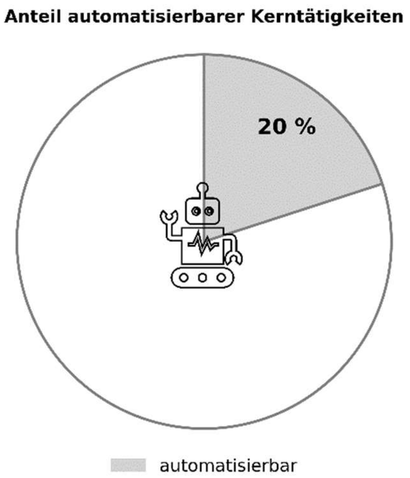
Appendix B: Figures and Tables

Appendix Figure A1: Visual representation of information



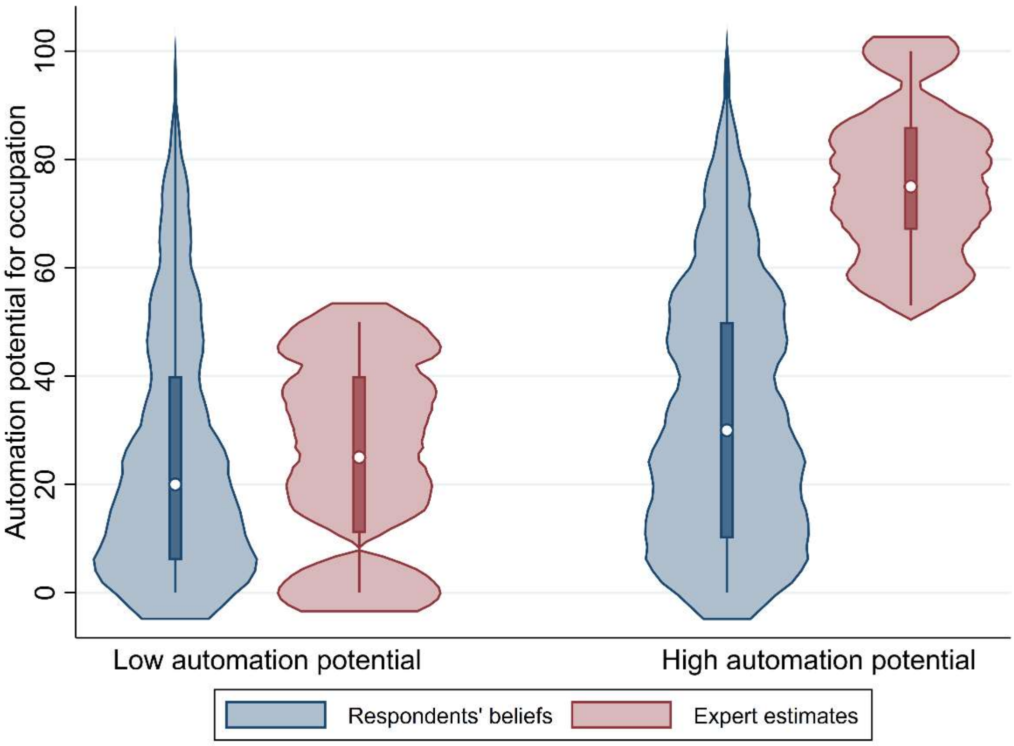
Notes: Experimental setup. Questions in bold are **primary outcomes** as specified in the AEA Registry AEARCTR-0009464.

Appendix Figure A2: Visual representation of information



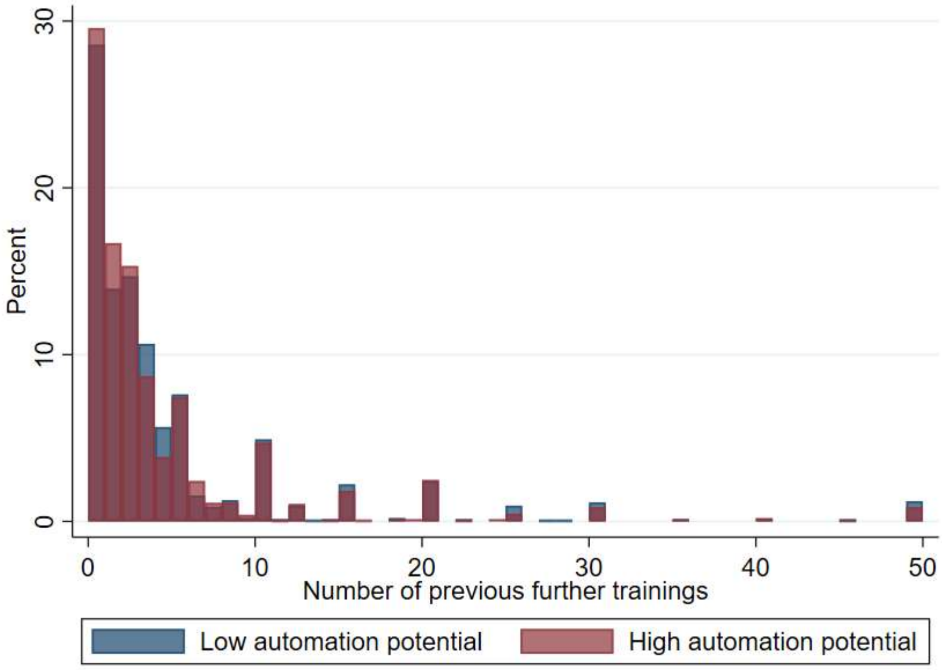
Notes: Example of the information about the occupation's automatability provided to the treatment group. This graph shows an example for an occupation with 20 percent automatable core tasks.

Appendix Figure A3: Distribution of respondents' beliefs and occupations' automatability for high- and low-automatable occupations



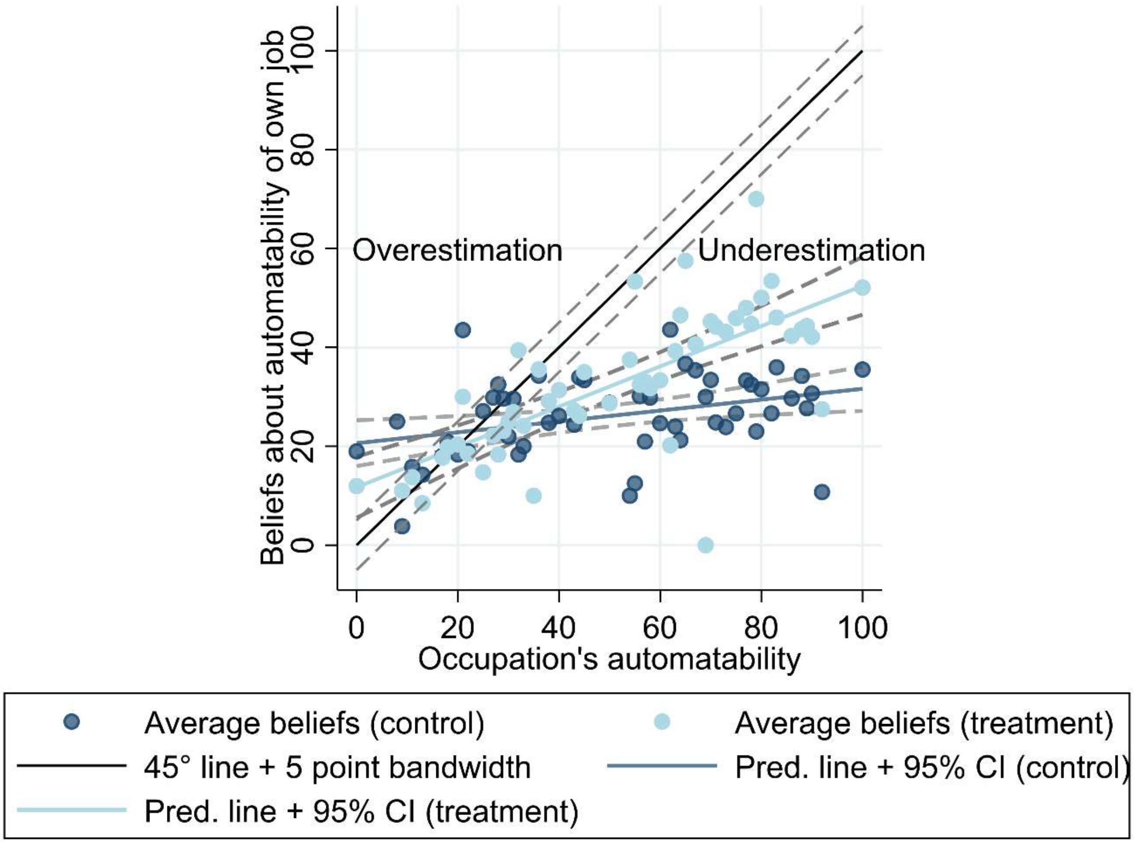
Notes: Blue shapes show the distribution of respondents' prior beliefs about their occupations' automatability, and red shapes show respondents' occupations' automatability according to expert estimates from the IAB, by respondents' occupations' automatability (high vs. low automatability). The box plots within the shapes show the median value and the interquartile range, with the extended lines representing upper- and lower-adjacent values. Data source: ifo Education Survey 2022.

Appendix Figure A4: Previous participation in further training



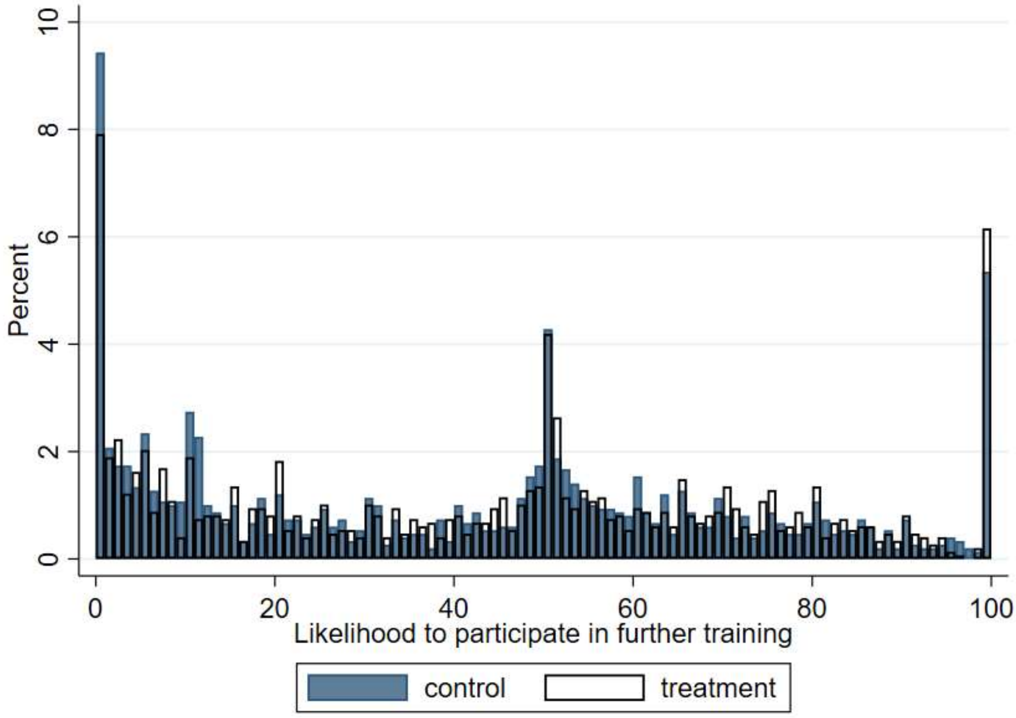
Notes: Previous participation in further training of respondents, divided into two groups: Those in occupations with high automatability (larger than 50 percent) and those in occupations with low automatability (less than 50 percent). Data source: ifo Education Survey 2022.

Appendix Figure A5: Respondents' beliefs vs. occupations' automatability by treatment group

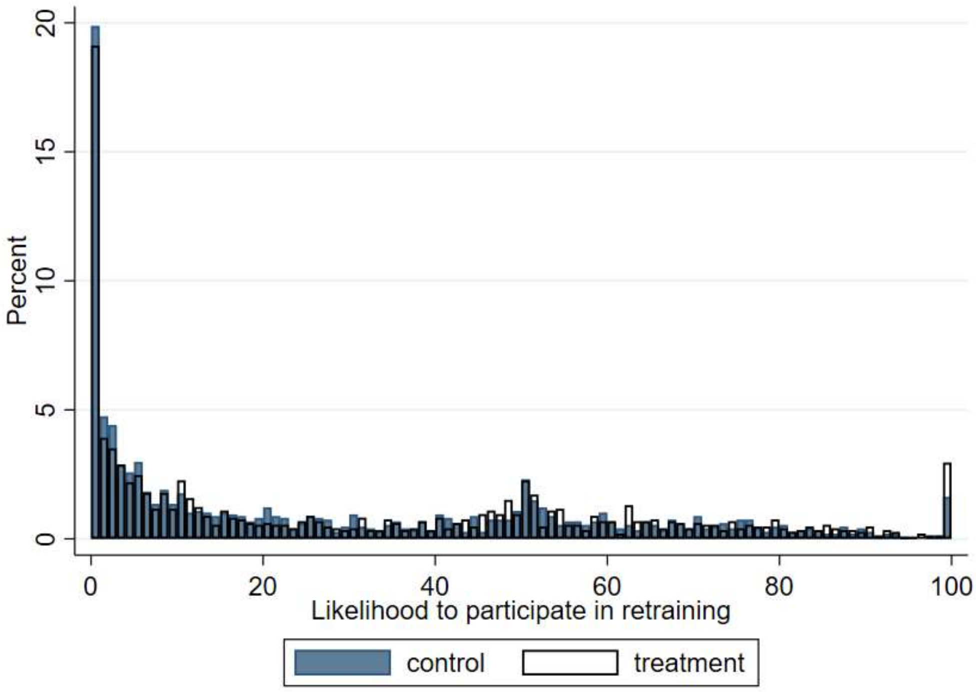


Notes: Respondents' answers to the question "*What do you think is the percentage of core activities that people perform in the profession [answer from earlier question about current occupation] that can be automated?*" are depicted as averages for each occupation's automatability (calculated by experts from the IAB), by respondents' treatment status. Randomized experimental treatment group: Respondents informed about the automatability of their occupations. The black line depicts the 45-degree line with a 5-point bandwidth. Points above the 45-degree line indicate an overestimation of the occupation's automatability and points below indicate an underestimation. Data source: ifo Education Survey 2022.

Appendix Figure A6: Likelihood of participation in further training and retraining



Panel (a) Further Training



Panel (b) Retraining

Notes: Respondents' answers to the questions "*How likely is it that you yourself will participate in further training of at least 120 hours within the next two years?*" and *"How likely is it that within the next two years you will complete retraining to another occupation?"* are depicted by respondents' treatment status. Randomized experimental treatment group: Respondents informed about the automatability of their occupations. Data source: ifo Education Survey 2022.

Appendix Table A1: Sample Balance

Control variable	Mean control	Mean treatment	Diff.	p-value
Age	42.65	42.98	0.33	0.49
Female	0.47	0.46	-0.01	0.67
Born in Germany	0.93	0.92	-0.02	0.12
City	0.37	0.40	0.03	0.11
Partner	0.64	0.65	0.02	0.35
Parent(s) with university degree	0.38	0.38	-0.01	0.77
Highest educational degree				
No degree/basic degree	0.24	0.26	0.02	0.16
Middle school degree	0.32	0.32	0.00	0.88
High school degree	0.44	0.42	-0.02	0.28
Employment status				
Fulltime	0.66	0.66	0.00	0.95
Parttime	0.22	0.23	0.01	0.50
Self-employed	0.07	0.05	-0.02	0.05
Unemployed	0.00	0.00	0.00	0.98
Retired/Ill/etc.	0.05	0.06	0.01	0.50
Parent status	0.54	0.54	-0.01	0.77
Party preference				
CDU	0.17	0.17	-0.01	0.61
SPD	0.18	0.17	-0.01	0.61
Grüne	0.13	0.12	-0.01	0.55
Linke	0.05	0.06	0.00	0.85
FDP	0.08	0.09	0.00	0.73
AfD	0.09	0.11	0.02	0.03
None	0.27	0.27	-0.01	0.57
Other	0.02	0.02	0.00	0.75
General voting	0.79	0.80	0.01	0.45
Patience	7.04	7.02	-0.02	0.84
Risk	5.72	5.78	0.06	0.51
Monthly Household Income (€)	2944.21	3014.03	69.82	0.26
West Germany	0.81	0.80	-0.01	0.56

Notes: Group means. 'Diff.' displays the difference in means between the control group and the treatment group who received the information about the automatability of their occupation. Data source: ifo Education survey 2022.

Appendix Table A2: Non-response

	Mean control	Mean treatment	Diff.	p-value
Labor-market expectations				
Concerned future	0.001	0.002	0.001	0.311
Other job tasks	0.000	0.001	0.001	0.157
Low risk unemployment	0.001	0.001	0.001	0.555
Automation tasks	0.000	0.001	0.001	0.317
Occupation existence	0.000	0.001	0.001	0.317
Higher wages	0.000	0.001	0.001	0.317
More demanding tasks	0.000	0.001	0.001	0.317
Less hours	0.000	0.001	0.001	0.157
More computer tasks	0.000	0.001	0.001	0.157
Need further training: all employees	0.001	0.000	-0.001	0.317
Need further training: same job employees	0.001	0.000	-0.001	0.317
Likelihood further training	0.015	0.011	-0.004	0.280
Likelihood retraining	0.029	0.027	-0.002	0.712
Policy proposal: compulsory further training	0.002	0.000	-0.002	0.083
Forgo wage	0.001	0.002	0.001	0.311
Information acquisition	0.000	0.001	0.001	0.157
Financial constraints	0.001	0.001	0.001	0.555
Time constraints	0.000	0.001	0.001	0.157
Employer constraints	0.000	0.001	0.001	0.317
FEA offered further training	0.000	0.001	0.001	0.317
Gains insecure	0.000	0.001	0.001	0.317
Great necessity	0.001	0.001	0.000	0.991
Confidence job future	0.000	0.001	0.001	0.317
Good measure structural change	0.001	0.001	0.000	0.991

Notes: Group means of item non-response. 'Diff.' displays the difference in means between the control group and the treatment group who received the information about the automatability of their occupation. Data source: ifo Education Survey 2022.

Appendix Table A3: Occupational Fields Respondents vs. German Population

Occupational Field	Share of respondents in respective field	Share of German population in respective field	Difference
Agriculture	1.59	1.50	0.09
Production & Manufacturing	14.18	20.71	-6.53
Construction & Architecture	4.02	6.10	-2.08
Natural Sciences	6.91	4.29	2.62
Transport	12.22	13.41	-1.19
Commercial Services	16.44	11.38	3.03
Administration & Organization	24.18	20.39	3.79
Health & Social Services	15.84	18.90	-3.06
Social Sciences	4.62	2.78	1.84

Notes: Shares of respondents in respective fields in respondent sample and in German population. Data sources: ifo Education Survey 2022 and Statistik der Bundesagentur für Arbeit 2022.

Appendix Table A4: Labor-Market Expectations

	Index LM concerns					Index work-environment change			
	Concerned future	Low risk unemployment	New tech replaces tasks	Job will not exist	Higher wage	Other tasks in job	More demanding tasks	Work less hours	More computer tasks
	(1)	(2)	(3)	(4)	(5)	(2)	(7)	(8)	(9)
Information	0.118*	0.006	0.254***	0.224***	0.022	0.246***	0.067	0.177***	0.195***
	(0.068)	(0.068)	(0.067)	(0.065)	(0.064)	(0.065)	(0.060)	(0.065)	(0.069)
Low Automation	-0.069	0.235***	-0.307***	-0.112*	0.158**	-0.128*	-0.085	-0.151**	-0.360***
	(0.069)	(0.069)	(0.066)	(0.064)	(0.065)	(0.066)	(0.062)	(0.065)	(0.071)
Information x Low Automation	-0.091	-0.025	-0.180*	-0.196**	0.055	-0.160*	0.029	-0.090	-0.078
	(0.098)	(0.096)	(0.094)	(0.092)	(0.090)	(0.094)	(0.087)	(0.093)	(0.100)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	2.438	3.458	2.563	2.001	3.269	2.814	3.206	2.291	3.231
Control share rather/fully agree	0.301	0.649	0.304	0.184	0.585	0.394	0.536	0.253	0.520
Observations	3008	3009	3011	3011	3011	3010	3011	3010	3010
R-squared	0.076	0.045	0.086	0.071	0.078	0.089	0.104	0.091	0.096
Information Effect for Low Automation	0.027	-0.019	0.074	0.028	0.077	0.086	0.096	0.087	0.117
	(0.070)	(0.068)	(0.066)	(0.065)	(0.064)	(0.068)	(0.063)	(0.066)	(0.072)

Notes: OLS regressions. Dependent variables (5-point scale: 1 = fully disagree, 5 = fully agree): (1) I am concerned about my professional future; (2) I have a low risk of becoming unemployed; (3) I am concerned that many tasks in my occupation will be replaced by new technologies; (4) I believe that my occupation will no longer exist in a few years; (5) I expect to be paid a higher wage in the future; (6) I will have different tasks in my occupation in the future than I have now; (7) I will work on more demanding tasks in the future; (8) I will work fewer hours in the future than I do now because some of my activities will be replaced by computers and computer-controlled machines; (9) In the future, I will work a lot with computers and computer-controlled machines. Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. Control share rather/fully agree: Dummy variable indicating the share of respondents answering rather or fully agree to the statement. See Table 1 for included covariates. Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01.

Appendix Table A5: Policy views

	Support compulsory further training		Further training is good strategy to cope with structural change		Need for further training will increase (all employees)		Need for further training will increase (same occupation)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Information	0.011	0.015	0.014	0.009	-0.015	-0.009	0.026	0.031
	(0.017)	(0.024)	(0.015)	(0.021)	(0.017)	(0.024)	(0.018)	(0.025)
Low Automation		0.035		0.015		-0.002		-0.037
		(0.024)		(0.022)		(0.024)		(0.025)
Information x Low Automation		-0.010		0.010		-0.011		-0.010
		(0.034)		(0.030)		(0.034)		(0.036)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	0.625	0.605	0.767	0.760	0.662	0.654	0.504	0.514
Observations	3009	3009	3010	3010	3011	3011	3011	3011
R-squared	0.059	0.060	0.054	0.054	0.053	0.054	0.051	0.053
Information Effect for Low Automation		0.005		0.019		-0.020		0.021
		(0.024)		(0.021)		(0.024)		(0.026)

Notes: OLS regressions. Dependent variables: (1) – (2) Policy proposal: Obligation for all employees affected by structural change and digitalization to participate in further training (dummy coded one if agree); (3) – (4) Further training is a good way to keep pace with structural change; (5) – (6) Need for further training for all employees (dummy coded one if increase); (7) – (8) Need for further training for employees in same occupation as oneself (dummy coded one if increase); Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Using the full variation of the 5-point Likert scale does not change the interpretation of the results; Baseline mean: Mean of the variable in the control group or baseline group. See Table 1 for included covariates. Outcomes in this table are pre-registered as secondary outcomes. Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A6: Barriers to training participation (I)

	Financial constraints		Time constraints		Employer constraints		Offered by FEA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Information	0.014	0.035	0.003	0.020	-0.013	-0.018	-0.001	0.004
	(0.018)	(0.025)	(0.017)	(0.024)	(0.018)	(0.025)	(0.018)	(0.025)
Low Automation		0.003		0.008		-0.039		0.008
		(0.025)		(0.024)		(0.025)		(0.025)
Information x Low Automation		-0.041		-0.035		0.011		-0.010
		(0.035)		(0.034)		(0.035)		(0.035)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	0.454	0.457	0.352	0.345	0.450	0.473	0.395	0.390
Observations	3009	3009	3010	3010	3011	3011	3011	3011
R-squared	0.068	0.068	0.046	0.046	0.074	0.075	0.026	0.026
Information Effect for High Automation		-0.006		-0.015		-0.007		-0.006
		(0.025)		(0.024)		(0.025)		(0.025)

Notes: OLS regressions. Dependent variables (dummy = 1 if person fully or somewhat agrees): (1) – (2) I cannot financially afford to attend further training; (3) – (4) I do not have time for further training (e.g., because of caring for relatives, childcare, etc.); (5) – (6) My employer does not offer me the opportunity for professional development; (7) – (8) I do not wish to participate in any further vocational training funded by the Federal Employment Agency (FEA); Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. See Table 1 for included covariates. Outcomes in this table are pre-registered as secondary outcomes. Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A7: Barriers to training participation (II)

	Confident about professional future		Great necessity to participate in further training		Unsure about returns to training	
	(1)	(2)	(3)	(4)	(5)	(6)
Information	-0.007	-0.020	-0.005	0.026	0.010	0.032
	(0.017)	(0.024)	(0.018)	(0.025)	(0.018)	(0.026)
Low Automation		0.014		0.069***		-0.000
		(0.024)		(0.025)		(0.026)
Information x Low Automation		0.027		-0.063*		-0.044
		(0.034)		(0.035)		(0.036)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	0.665	0.658	0.475	0.435	0.476	0.481
Observations	3011	3011	3010	3010	3011	3011
R-squared	0.052	0.053	0.069	0.071	0.019	0.020
Information Effect for Low Automation		0.007		-0.037		-0.012
		(0.024)		(0.026)		(0.026)

Notes: OLS regressions. Dependent variables (dummy = 1 if person fully or somewhat agrees): (1) – (2) I am unsure whether further training will pay off for me; (3) – (4) I see a great need to participate in further training; (5) – (6) I am well equipped for my future; Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. See Table 1 for included covariates. Outcomes in this table are pre-registered as secondary outcomes. Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01.

Appendix Table A8: Information effect on information acquisition

	Information acquisition	**Information acquisition**
	(1)	(2)
Information	0.002	0.029
	(0.017)	(0.024)
Low Automation		0.059**
		(0.025)
Information x Low Automation		-0.056
		(0.035)
Covariates	Yes	Yes
Baseline Mean	0.386	0.350
Observations	3010	3010
R-squared	0.066	0.068
Information Effect for Low Automation		-0.027
		(0.025)

Notes: OLS regressions. Dependent variables: (1) – (2) Information acquisition; Randomized experimental treatment group "Information": respondents informed about automatability of occupation. Baseline mean: Mean of the variable in the control group or baseline group. See Table 1 for included covariates. Outcomes in this table are pre-registered as secondary outcomes. Data source: ifo Education Survey 2022. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.