When the Tax Machine Cometh: Who Benefits from Automation?*

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Abstract

We provide experimental evidence on how employers adjust expectations to automation risk in high-skill, white-collar work. Using a randomized information intervention among tax advisors in Germany, we show that firms systematically underestimate automatability. Information provision raises risk perceptions, especially for routine-intensive roles. Yet, it leaves short-run hiring plans unchanged. Instead, updated beliefs increase revenue and profit expectations without wage adjustments, implying limited rent-sharing. Employers also anticipate new tasks in legal tech, compliance, and AI interaction, and report higher training and adoption intentions. Our findings reveal how employer beliefs shape anticipatory responses to technological change.

Keywords: Automation, Labor Demand, White Collar Jobs, Human Capital Investment, Technological Displacement
JEL classification: J23, J24, O33, C93

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1 Introduction

Digital technologies have become a key driver of economic growth, but their rapid diffusion is transforming the structure of labor markets in profound ways. Emerging technologies such as generative artificial intelligence (GenAI) are increasingly capable of automating complex cognitive tasks, raising critical questions about their impact on employment, wage structures, and skill requirements.

Historically, automation has primarily affected blue-collar jobs in manufacturing and manual labor-intensive sectors, where robotics and mechanization replaced routine tasks (e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021). However, the latest wave of AI-driven automation differs markedly: highly educated, high-income white-collar occupations are now among the most exposed (e.g. Eloundou et al., 2024). Recent studies suggest that AI assistance can significantly enhance worker productivity in professional settings. For instance, Noy and Zhang (2023) show that AI-assisted writers complete tasks faster and produce higher-quality output, while Brynjolfsson et al. (2025) document a 14 % productivity increase among customer service agents using generative AI, with the largest gains among less-experienced workers. At the same time, Felten et al. (2023) highlight that occupations relying on communication, analysis, and creative abilities - once considered resistant to automation - are now highly susceptible to AI-driven disruption.

Despite the growing literature on automation's effects, most existing studies focus on workers rather than employers. Little is known about how firms perceive and respond to automation risks, although evidence on this is crucial because employer expectations directly shape labor demand and technology adoption. To investigate this, we study tax consulting—a white-collar, high-skill setting where generative AI is particularly relevant given the prevalence of structured and repetitive tasks. A key advantage of this setting is the availability of granular occupational categories at the five-digit level, which enables us to distinguish between tax clerks, certified tax assistants, tax advisors, and auditors. This granularity reduces bias from occupation-task mismatches and allows us to capture heterogeneity in automation exposure across different expertise levels. In this setting, we exogenously shift employers beliefs about automation rates using a randomized information intervention. Our survey, which targeted the entire population of tax advisors and auditors listed in Germany's official register, allows us to analyze how belief updates about automation potential influence employment, wage, and firm expectations. Additionally, we examine firm-level outcomes such as revenue, profits, and costs to assess whether employers view automation as an opportunity for efficiency gains or a disruptive force of workforce reductions.

By contextualizing our findings within a task-based automation framework, this study provides fresh insights into how automation reshapes firm decision-making and labor market dynamics. Moreover, we investigate how and if individuals respond to automation, by investigating plans for training employees. Further training is a crucial component to benefit from the potential technological disruption, but also new orientation on the labor market could happen, since existing skills become obsolete and also some professions might be endangered.

Our results reveal several striking patterns. First, employers systematically underestimate automation risks for their profession. Initial beliefs about the share of tasks that could be automated within the next decade are significantly lower than expert assessments. After receiving objective information on automation potential from the research institute of the German Federal Employment Agency (IAB), respondents revise their beliefs upward, particularly for lower-skilled roles such as tax clerks and certified tax assistants. Belief updating is weaker for higher-skilled occupations like auditors and tax advisors, suggesting that firms perceive greater barriers to automation at the top of the professional hierarchy.

Interestingly, cost expectations also rise, indicating anticipated investments in new technologies or upskilling initiatives. However, wage expectations remain unchanged, suggesting that firms intend to retain productivity gains rather than pass them on to employees.

Second, despite updating their beliefs about automation, firms do not immediately revise their hiring or firing plans, indicating that automation-induced workforce displacement are not a primary concern in the near term. However, firms do expect a significant decrease in the change of task content by 20 % of tasks for tax advisors and about 60 % of tasks for certified tax assistants by 2027. Belief shifts are associated with a significant increase in productivity, indicating an increase in labor demand from non-automated tasks. This is consistent with the notion that efficiency gains from automation may enhance firm performance rather than lead to immediate labor displacement. Especially for the certified tax assistant, an increase in non-automated tasks is expected by 7 percentage points. This is in line, with the notion that employers do not replace low-skilled workforce with artificial intelligence. Interestingly, cost expectations also rise, indicating anticipated investments in new technologies or upskilling initiatives.

Third, firms exposed to new information on automation not only reassess existing job roles but also anticipate new tasks emerging as a consequence of AI adoption. In particular, employers expect increased demand for legal tech expertise, compliance monitoring, and AI interaction skills such as prompt engineering. This aligns with a growing recognition that generative AI does not merely replace existing jobs but also reshapes job content and skill requirements.

Fourth, employers exposed to automation information are significantly more likely to report plans for further training and upskilling investments for their staff. Our results show that belief updating about automation not only shifts expectations about task content but also increases the likelihood that firms intend to invest in specialized digital skills, legal tech, and AI-related training. At the same time, treated firms report a greater openness toward adopting AI solutions and perceive automation more as an opportunity than as a threat.

The results we find on perceptions, expectations, and intentions translate into actions. Firms that plan to adopt AI tools also actively search for AI solutions. Although not all firms plans to hire, e.g., tax clerks result in job ads, all firms that post job ads on the official job portal of the German Federal Employment Agency also indicate to plan hiring in our survey.

Our study contributes to three strands of research. First, we extend the literature on automation and labor markets. Much of this literature focuses on the effects of automation in manufacturing and manual labor-intensive sectors. For example, Acemoglu and Restrepo (2020) find that increased robot adoption in US. manufacturing is associated with significant reductions in employment and wages, with localized displacement effects that are not fully offset by gains in other sectors. In contrast, Dauth et al. (2021) examine the impact of robots in Germany, finding job losses in manufacturing but compensating employment gains in service industries. Further studies uncover interesting heterogeneities in automation's effects (see Aghion et al., 2022, for a survey of the recent literature).

For instance, Bessen et al. (2020) demonstrate that firms adopting automation technologies often save labor while maintaining wage growth. Similarly, Koch et al. (2021) find that robot adoption in Spanish manufacturing firms leads to significant output gains and net job creation, suggesting that automation can enhance productivity without necessarily reducing employment. Aghion et al. (2020) further show that automation in French manufacturing increases employment at the firm and industry levels, with productivity effects outweighing displacement effects. At the same time, recent evidence suggests that AI adoption may increase wage inequality, with high-wage workers benefiting disproportionately while low-wage and production workers face negative employment effects (Bonfiglioli et al., 2024). Unlike robotics, which primarily automated routine manual tasks, AI influences both routine and non-routine cognitive tasks. Arntz et al. (2016) decomposes occupations into detailed task shares to estimate automation susceptibility across OECD countries. Gathmann et al. (2024) show that AI reduces abstract tasks like information gathering while increasing the need for high-level routine tasks that require monitoring and process oversight. Our study extends this literature to white-collar industries, suggesting that GenAI-driven automation might enhance efficiency without triggering immediate job losses. Moreover, unlike manufacturing automation, which primarily substitutes for low-skill tasks, generative AI influences a broader spectrum of occupational roles, including highly skilled professions.

Second, our study takes a novel employer-centered perspective, which allows us to detect potential adjustments in hiring plans, wage strategies, and skill investment decisions before they materialize as measurable labor market outcomes. This is particularly valuable because the existing literature, while rich in documenting the impacts of automation at the worker and firm levels, often examines outcomes only after automation technologies have been implemented. For example, Bessen et al. (2025) examine worker-level outcomes following firm-level automation expenditures, finding significant impacts on worker displacement and cumulative wage losses. Similarly, Acemoglu et al. (2022) analyze the adoption of AI using vacancy-level data, demonstrating shifts in hiring patterns and skill requirements at AI-exposed establishments between 2010 and 2018. However, their analysis does not extend to the most recent wave of generative AI adoption, leaving open questions about how firms anticipate and adapt to these transformative technologies. Although, these approaches are invaluable for understanding post-adoption consequences, it does not shed light on how firms plan for or adapt to automation before investments are made. Our study instead captures firms' anticipatory responses, showing that automation beliefs influence business expectations and investment strategies before observable adjustments occur.

Our study methodologically builds upon the literature employing information interventions to examine how accurate data can correct misperceptions and influence economic preferences and behaviors (e.g. Alesina et al., 2022; Kuziemko et al., 2015; Coibion et al., 2018; Wiswall and Zafar, 2015). Within this framework, recent research has focused on how information about automation affects individual expectations and behaviors. Similarly, Jeffrey (2021) shows that the framing of automation influences policy preferences, with narratives of inevitable displacement increasing support for redistribution. Furthermore, Lergetporer et al. (2023), which is closest to our study, since it relies on the same automatability measure, demonstrate that workers often underestimate the automatability of their occupations. They also show that providing personalized information to households about automation risks increases their willingness to engage in further training. Relative to this study, we treat employers and focus on firm outcomes including training for employees with relevant automatability risk instead of targeting the general population. Moreover, we our experimental design allows to estimate a Bayesian updating model within an instrumental variables (IV) framework. Furthermore, we also contribute to the literature on the relationship between automation and further training. (Sotiris et al. (2019), Innocenti and Golin (2022), Lergetporer et al. (2023)). Our study extends this literature by shifting the focus to employers, examining how updated beliefs about automation potential influence business expectations, labor market expectations, and individual responds behavior to cope with automation in a white-collar industry.

The remainder of this paper is organized as follows. Section 2 describes the survey, experimental setup, and estimation strategy. Section 3 presents the results, while Section 4 concludes.

2 Survey and Experimental Setup

2.1 The GBP Tax Advisor Survey

Our analysis draws on a specialized survey of tax advisors conducted between November 2024 and April 2025. As part of the German Business Panel (GBP), this survey targeted all professionals listed in Germanys official register of licensed tax advisors (*Steuerberater*) and auditors (*Wirtschaftsprüfer*), leveraging over 80,000 email addresses from the register. Since the official register is both mandatory and exhaustive, it covers all individuals and firms authorized to practice as tax advisors and auditors in Germany.

In Germany, tax advisors are classified as *Freiberufler* (liberal professionals), a designation that differentiates them from traditional firms. Freiberufler, including tax advisors, lawyers, and doctors, constitute a highly organized and economically significant part of the service sector: as of January 2023, about 1.47 million self-employed professionals in these fields accounted for roughly 3% of the workforce, employing around 4.2 million people and generating over 10% of Germanys GDP.[1] While tax advisors operate independently under distinct legal and tax frameworks, they frequently employ significant numbers of workers, playing a vital role in the labor market. However, standard firm-level datasets, such as those used in business or employer-employee panel studies, typically exclude *Freiberufler*, creating a significant data gap. Using the mandatory register for fielding allows us to bridge this gap, offering direct insights into this unique professional group and their responses to automation in a new custom survey.

Survey Modality and Data Collection Process The survey was distributed via the survey software provider Qualtrics through the German Business Panel infrastructure. Upon the survey invitation, participants are asked to answer the survey questions carefully and are assured that their participation is voluntary. We inform them that the survey should take (on average) 10 minutes. Prior to the start of the survey, all participants

[1] Professional chambers oversee admission, standards, and representation for liberal professions, underscoring their central role in the German labor market.

regardless of treatment assignment were shown a short, neutral 30-second video by the president of the tax advisors association highlighting the relevance of AI for the profession. The videos sole purpose was to encourage engagement with the survey content and did not contain persuasive or experimental elements.

The survey was conducted online and designed to be accessible across multiple devices, including desktop computers, tablets, and smartphones. The interface was optimized for both large and small screens to ensure a high user experience across different devices.

To manage outreach effectively, we distributed the survey in weekly batches starting in November 2024. Each respondent received up to three reminders if they had not completed the survey: the first one week after the initial invitation, the second two weeks later and the third one month later. This structured follow-up approach helped maximize response rates while preventing excessive survey fatigue. This was followed by a thank you email, when finishing the survey. The median survey completion time was 693 seconds (approximately 11.55 minutes), which aligns well with the expected 10-minute duration. While most respondents completed the survey promptly after receiving their invitation, a subset only finalized their responses after receiving a reminder. These delayed completions resulted in some extreme duration values, as certain participants resumed the survey days or even weeks after initially opening it.

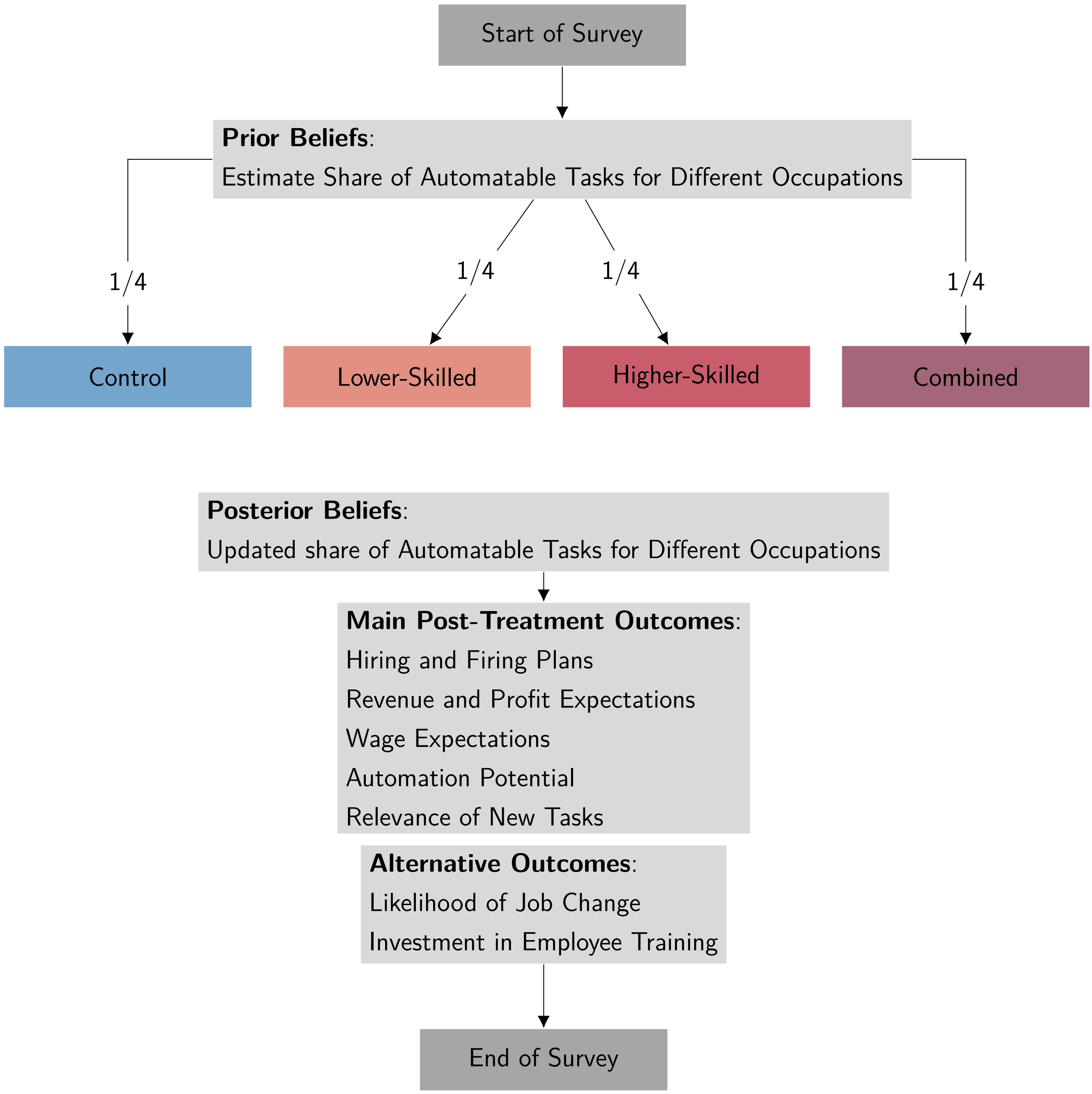
2.2 Experimental Setup

The key part of our survey is a randomized information intervention designed to examine how the firms of the tax advisory industry respond to updated information on the automation potential of their workforce. The experiment follows the sequence, visually represented in Figure 1.

Before the intervention, we collect respondents' employment levels and their prior beliefs about the automatability of four tax-related occupations: tax clerks, certified tax assistants, tax advisors, and auditors. Participants estimate the percentage of core activities within each occupation that they believe can be automated as of 2024.

Following this, respondents are randomly assigned to one of three treatment groups or a control group, each with equal probability. The treatment groups receive personalized information about the automatability of each occupation, based on occupation-level estimates from the IAB Job-Futuromat.

Figure 1: Experimental Design



Notes: The figure illustrates the design of our information treatment.

The IAB Job Futuromat The IAB Job-Futuromat is a tool developed by the Institute for Employment Research (IAB), a research division of Germany's Federal Employment Agency. It provides a systematic assessment of how digital technologies impact various occupations by evaluating the degree to which specific tasks within those roles can be automated. It covers approximately 4,000 occupations and is based on expert-driven task analyses, making it one of the most detailed and policy-relevant resources on labor automation.

The automatability scores in the Job-Futuromat are built on BERUFENET data, an expert database maintained by the German Federal Employment Agency, which documents occupational tasks, required skills, and competencies for career guidance and job placement. The methodology behind BERUFENET, as described by Dengler et al. (2014), follows a task-based approach similar to O*NET in the U.S., systematically mapping occupations to their core tasks and assessing their substitutability by automation.[2] This expert-driven approach offers a robust alternative to survey-based task measurements, ensuring that occupational analyses remain consistent and reliable over time.

Research using Job-Futuromat data has revealed that occupations with higher substitutability potential tend to experience lower employment growth on average (e.g. Dengler and Matthes, 2021; Grienberger et al., 2020).[3] It has also been used in an information experiment by Lergetporer et al. (2023), who study how workers adjust their training and upskilling demand when they learn the automatability of their occupation.

Table 1: Automation potential of tax occupations according to the Job-Futuromat.

Occupation	**Automation Potential**
Tax Clerk (Steuerfachangestellter)	100%
Certified Tax Specialist (Steuerfachwirt)	80%
Tax Advisor (Steuerberater)	62%
Auditor (Wirtschaftsprüfer)	57%

Note: See Figure A.1 for screenshots of the IAB Job-Futuromat.

The automation potential estimates for the four tax-related occupations considered in this study are strikingly high (see Table 1). According to the Job-Futuromat, tax clerks face a complete automation risk (100%), while certified tax specialists also exhibit a high substitutability potential (80%). Even among higher-skilled roles, tax advisors (62%),

[2]The automatability of an occupation is obtained by first dividing the number of automatable core tasks of an occupation by all its core tasks and multiplying the result by 100. This is known as the substitution potential. Only the core tasks of this occupation are taken into account in the calculation. It is assumed that each core task is performed with the same frequency and therefore has the same influence on the calculation of automatability of an occupation o.

$$\text{automatability}_o = \frac{\text{Number of core tasks that can be automated}_o}{\text{Number of all core tasks}_o} \times 100.$$

We accessed the Job-Futuromat in November 2024. All specifications on automatability refer to the technological possibilities existing in 2022.

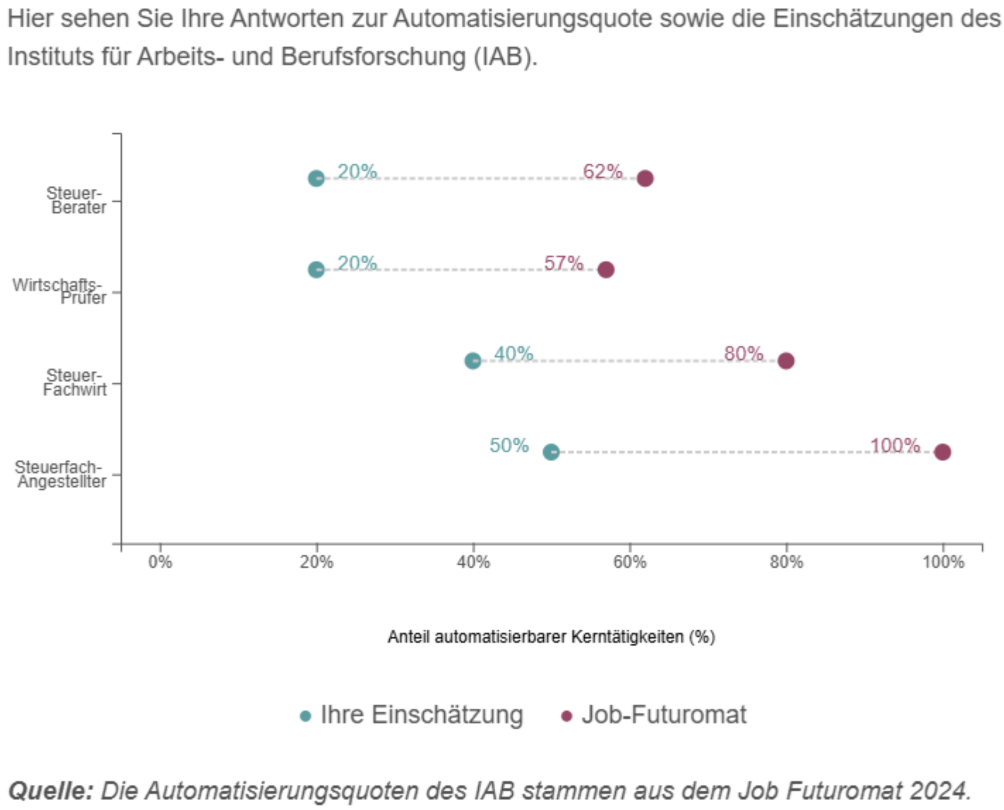
[3]However, some highly automatable professions have still seen employment growth, indicating that factors beyond technological feasibility, such as economic demand, regulatory environments, and skill shortages, play a crucial role in the adoption of automation.

and auditors (57%) show considerable exposure to automation.

The Information Treatment To examine how individuals respond to expert-provided automation assessment, we implement an information treatment that randomly assigns respondents into one of four groups including a passive control group. Respondents assigned to one of the three treatment arms receive an animated visualization comparing their own estimates of the automation potential in their occupation to expert assessments from the Institute for Employment Research (IAB). The treatment heading states: *"Here you can see your answers on the automation rate, along with the assessments of the Institute for Employment Research (IAB)"*.

1. **Control Group:** Only respondents' own beliefs are displayed.
2. **Lower-Skilled Treatment:** Respondents' beliefs are compared with expert assessments for tax clerks and certified tax assistants.
3. **Higher-Skilled Treatment:** Respondents' beliefs are compared with expert assessments for tax advisors and auditors.
4. **Combined Treatment:** A comprehensive visualization comparing prior beliefs and expert assessments for all four listed occupations.

Figure 2: Example Screenshot of the Information Treatment



Note: This figure presents a screenshot of the combined treatment animation.
Source: German Business Panel Screenshot

The visualization consists of a dumbbell plot (see Figure 2 for an example screenshot for the "combined treatment" arm) where each occupation is represented by a horizontal line connecting two color-coded points. The animation unfolds smoothly, starting with respondents' own beliefs and then progressively revealing the objective IAB values, visually emphasizing the gap between the two.[4] The animation design follows best practices in visual perception research, using motion to guide attention while avoiding excessive cognitive load. For the control group only a static plot is displayed, showing the own beliefs of the respondents graphically.

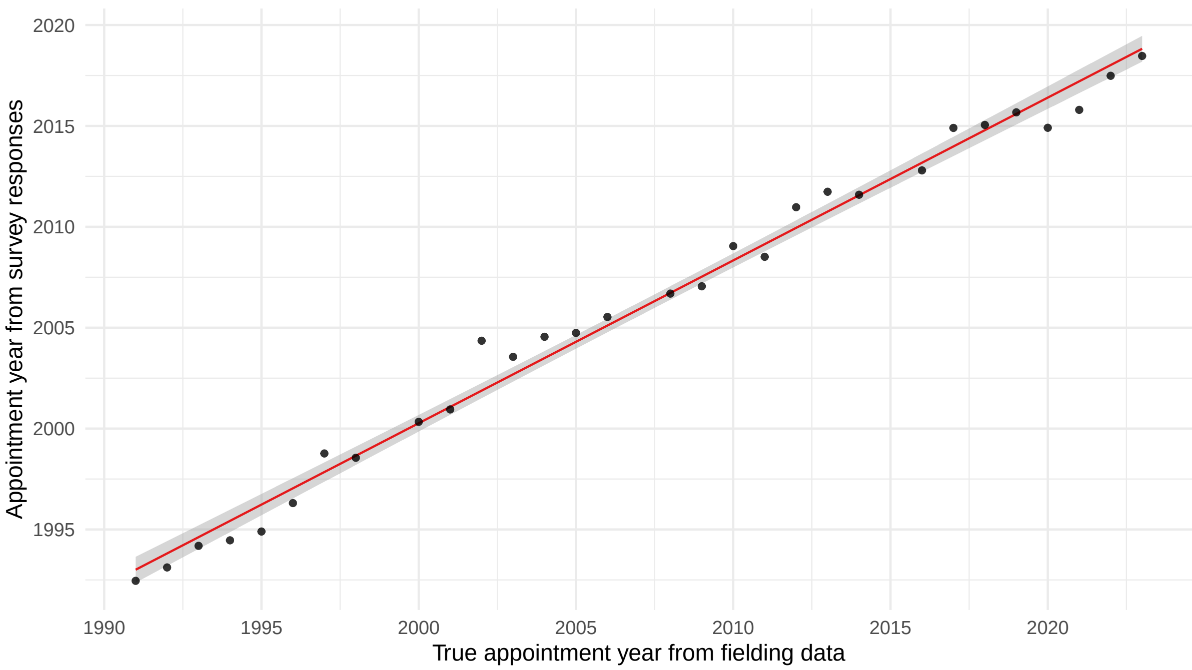
After the experiment, we ask whether respondents want to update their beliefs to elicit a posterior for all 4 occupations. We then proceed with several questions on hiring and firing, revenue, profit and cost and wage expectations as well as perceived automation potentials and new tasks due to automation.

[4]The visualization is implemented using `d3.js`, a JavaScript library for producing dynamic, interactive data visualizations in web browsers (Bostock et al., 2011).

2.3 Data Quality and Plausibility Checks

Ensuring the reliability and representativeness of our survey data is crucial for deriving meaningful insights about tax advisory firms.

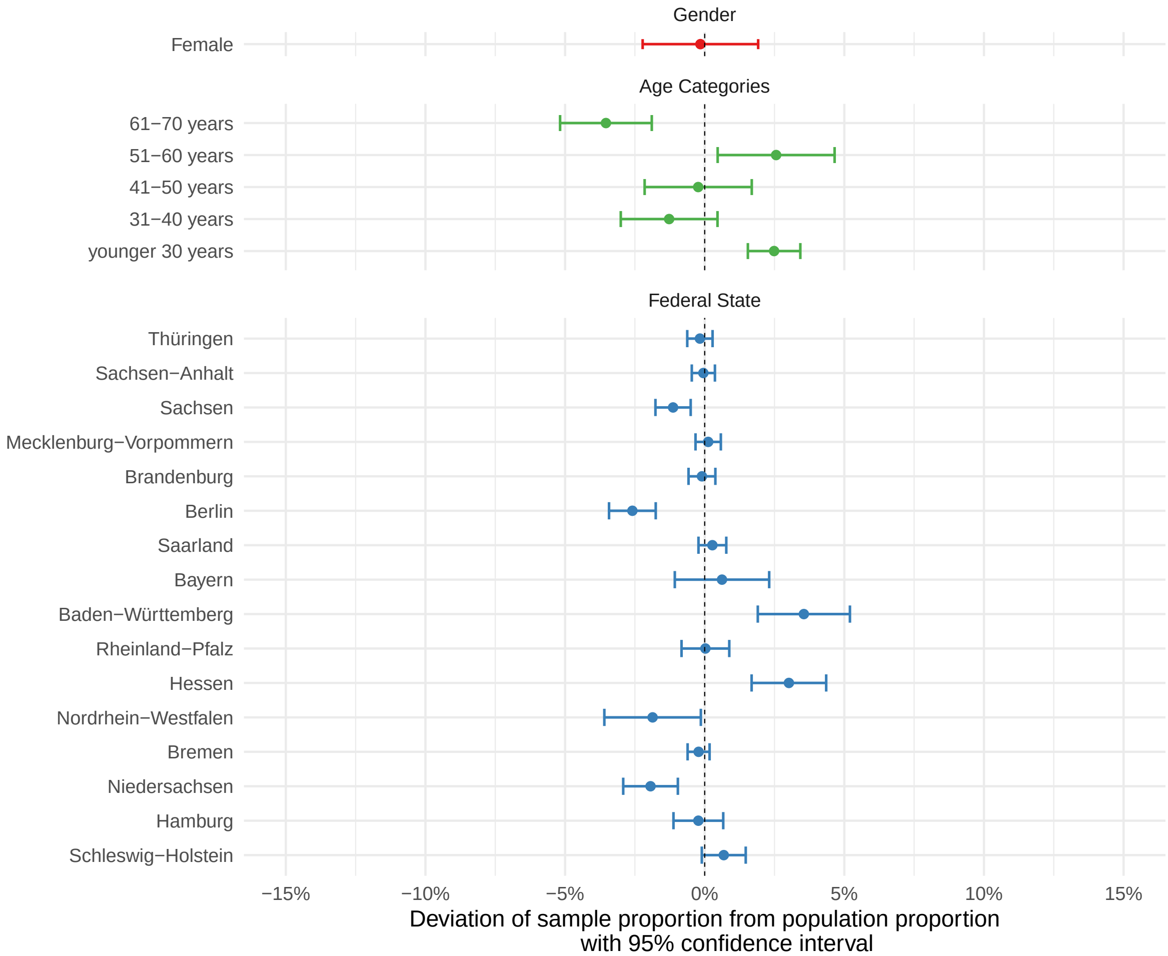
Figure 3: Survey and register data



Note: This figure presents a binned scatter plot comparing self-reported appointment years from the survey with official register data. Each point represents the average self-reported appointment year within 30 equally sized bins of the true appointment year from the register data. A linear fit in red, demonstrates a strong positive correlation, indicating high consistency between self-reported and official records. Deviations are most pronounced among respondents with early appointment years, likely reflecting inactive professionals who retain their designation.
Source: German Business Panel Tax Advisor Survey 2025 and German Registers of Tax Advisors

Consistency with Register Data A critical test of our dataset's accuracy is the alignment between self-reported and official register data. To this end, we compare survey answers on the appointment year as tax advisor to the official register entry for each respondent. We check this in a binned scatter-plot in Figure 3, which reveals a strong positive correlation, reflecting the reliability of responses. The red trend line and confidence interval suggest that, for the majority of respondents, self-reported data closely matches the fielding data from the register. Extreme deviations are rare and especially present for the oldest respondents in our sample (i.e. the early appointment years), who are unlikely to still be economically active as tax advisors. To prevent inconsistencies, we restricted the data to cases where the reported appointment years deviated by no more than five years from the register.

Figure 4: Representativity of the survey



Note: This figure compares key demographic characteristics of survey respondents with population benchmarks from the official statistics of the Chamber of Tax Advisors, with whiskers representing 95% confidence intervals. The plotted coefficients represent differences in respondent proportions relative to the population across categories such as gender, age groups, and federal states.
Source: German Business Panel Tax Advisor Survey 2025 and Official Statistics of the Chamber of Tax Advisors

Sample Representativeness Across Key Demographics To ensure our survey sample reflects the broader population of tax advisory and auditing firms, we compared sample proportions with population benchmarks from the official statistics of the chamber of tax advisors. Figure 4 illustrates deviations across self-employment status, gender, age categories, and federal states. The results demonstrate that the survey largely captures the target population, with most deviations falling within acceptable ranges. These differences primarily stem from the nature of the official register and our focus on economically active tax and auditing firms. For instance, since the titles of tax advisor and auditor are lifelong, many older professionals retain their designation despite no longer being active.

We have also obtained balance sheet data for firms who completed the survey if available using data from the Bureau van Dijk Orbis database. Although the Orbis data are often only observed irregularly and sometimes up to six years prior to the survey, Figure F.2 they show high agreement for the measures of the number of employees and of log revenue as reported in Orbis and in the survey. This further shows that stated and actual values correspond very well.

Filtering and Cleaning Steps While the overall data quality is high and the survey is representative of the target population we intend to capture, some filtering and cleaning was still needed. Across all filtering steps, our goal was to ensure that only active tax advisory firms remained in the dataset while excluding respondents who are in the professional register but do not operate in the relevant business segment.

First, we screened for information in open occupation and legal form fields in our survey to excluded respondents whose occupations (e.g., retirees, university professors) or organizational roles (e.g., heads of large corporate tax departments) did not align with the target population.

Second, we applied revenue plausibility checks. Firms reporting revenue below 25,000 EUR were excluded, as such values indicate economic inactivity.[5] Likewise, firms with revenues exceeding 15 million EUR or unusually high revenue per employee were flagged for manual review. Many of these cases involved corporate tax departments of firms in other economic sectors rather than independent tax firms, introducing potential bias. Where open responses or contact details confirmed this, we excluded them from the sample.

In addition, respondents who reported employment Figures above 150 or revenues above 10 million Euros at their firms were reviewed, as they likely represented outliers compared to typical tax firms. Interestingly, most of these respondents are working at large international auditing firms. While we include these observations in the survey, we run most of the analyses only for smaller firms, since we only have 148 observations for these larger firms.

Finally, we excluded a small number observations with obviously erroneous answers. These included only a small number respondents who stated that they fire more than 100% of their workforce, expect revenue and cost decreases of more than 100% or cross-referenced

[5]These respondents were typically beyond the typical retirement age for tax advisors, reflecting the ability of registered advisors to maintain small advisory roles past retirement.

appointment year data with the appointment years stated in the register data, removing cases where reported appointment years deviated by more than five years.

After excluding these respondents and ensuring data consistency, the final sample currently consists of 1,736 observations.

2.4 Descriptive Statistics and Covariate Balance

The following Section presents a detailed descriptive analysis, offering insights into key demographic, employment, and revenue distributions.

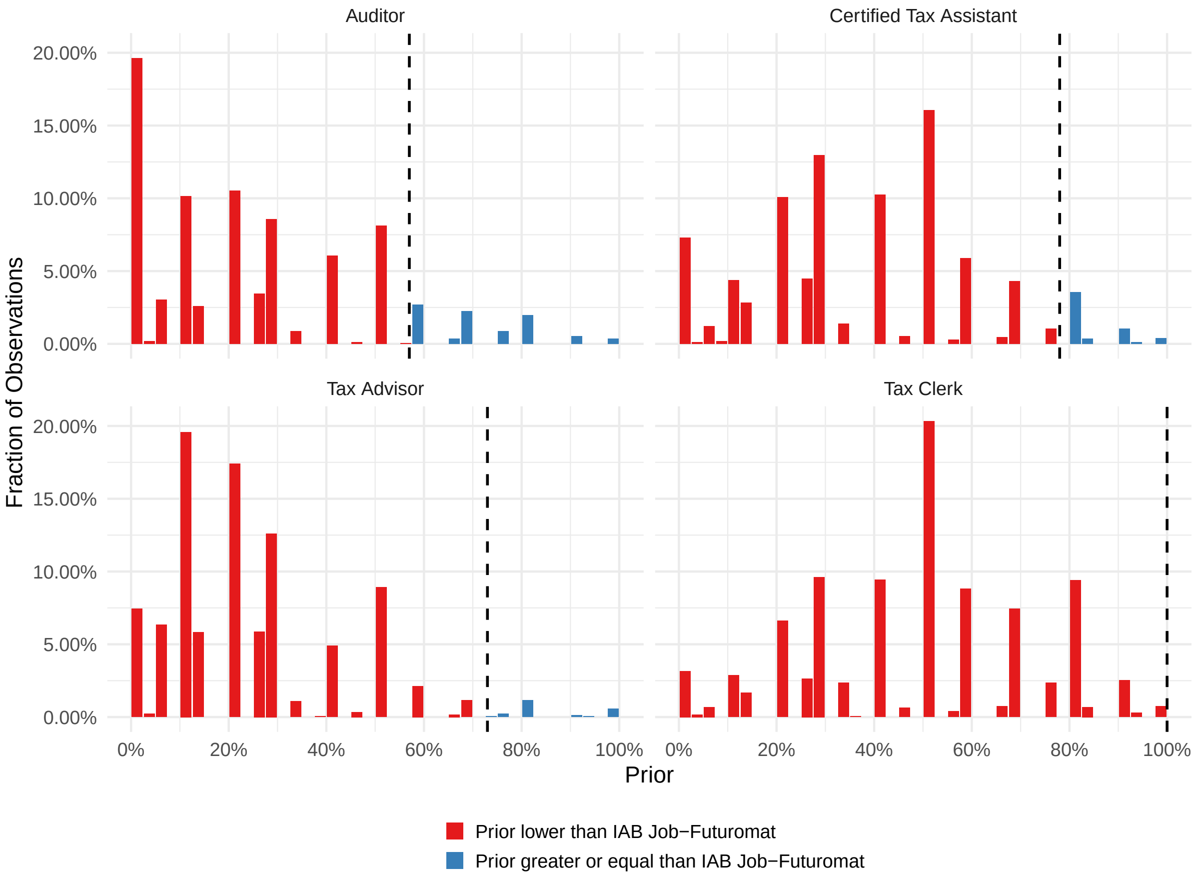
Summary Statistics The summary statistics presented in Table D.9 provide a comprehensive overview of the firms surveyed in the GBP Tax Advisor Survey. The average respondent is around 51 years old, with a strong representation of self-employed professionals (75%). Most respondents are tax advisors (98%), with a minority working in related auditing roles. Firm sizes vary significantly, with an average of 70 employees when all firms are included, though the distribution is highly skewed. The median employment is only 9 employees. Revenue statistics exhibit a similar pattern, with a median revenue of approximately 1 million euros but a mean exceeding 3 million euros due to high-revenue outliers among large firms. Female representation stands at 32%, reflecting broader industry demographics.

Revenue and Employment Distribution Figure A.2 visualizes the distribution of firm revenue (left) and total employees (right) in more detail for our main target group of smaller tax firms with less than 150 employees and revenues below 10 million Euros. The majority of firms have revenue below 2.5 million euros and employ fewer than 50 individuals, though some large firms, primarily large multinational auditing firms, contribute to a long right tail in both distributions.

Self-reported AI usage We also elicited self-reported AI usage. Figure A.4 in the Appendix shows the current use of generative AI across firms of different sizes. Among the smallest firms (0-4 employees), almost half report never using generative AI, and only 14.9% use it often or always. In contrast, larger firms (11-144 employees) show higher adoption rates, with less than 15% never using AI and 21.8% using it often or always.

Covariate Balance The covariate balance plot in Figure A.3 verifies the success of the randomization process. Mean differences between treatment arms and the control group remain small across all key firm characteristics, with confidence intervals largely overlapping zero. This ensures that any treatment effects observed in later analyses are not driven by pre-existing differences in firm size, revenue, or regional distribution. The balance in employment and revenue distributions further underscores the robustness of the experimental design.

Figure 5: Distribution of Prior Beliefs



Note: This figure displays the distribution of prior beliefs about job automatability for four tax-related occupations: Tax Clerk, Certified Tax Assistant, Tax Advisor, and Auditor. The horizontal axis represents the subjective probability (prior belief) that a given occupation will be automated, while the vertical axis indicates the fraction of respondents reporting each probability level. The dashed vertical lines denote the automatability estimates from the IAB Job-Futuromat signal. The shading differentiates between respondents whose prior beliefs are below (blue) or at least as high (red) as the benchmark estimate. A large majority of respondents report priors below the IAB Job-Futuromat benchmark: 99.3% for Tax Clerks, 93.9% for Certified Tax Assistants, 97.7% for Tax Advisors, and 89.1% for Auditors.
Source: German Business Panel Tax Advisor Survey 2025

3 Results

Before analyzing how information influences tax advisors' expectations and decision-making, we first examine their prior beliefs about automation risks across different occupations.

Figure 5 illustrates the distribution of participants' prior beliefs regarding the share of automatable tasks in 2024 for tax clerks, certified tax assistants, tax advisors, and auditors. The vertical dashed lines represent expert assessments from the Institute for Employment Research (IAB), allowing for a comparison between subjective expectations and the expert signals. Across all occupations, most respondents underestimate automation risks, with only a small minority assigning higher probabilities than the expert signals.

3.1 Information Updating

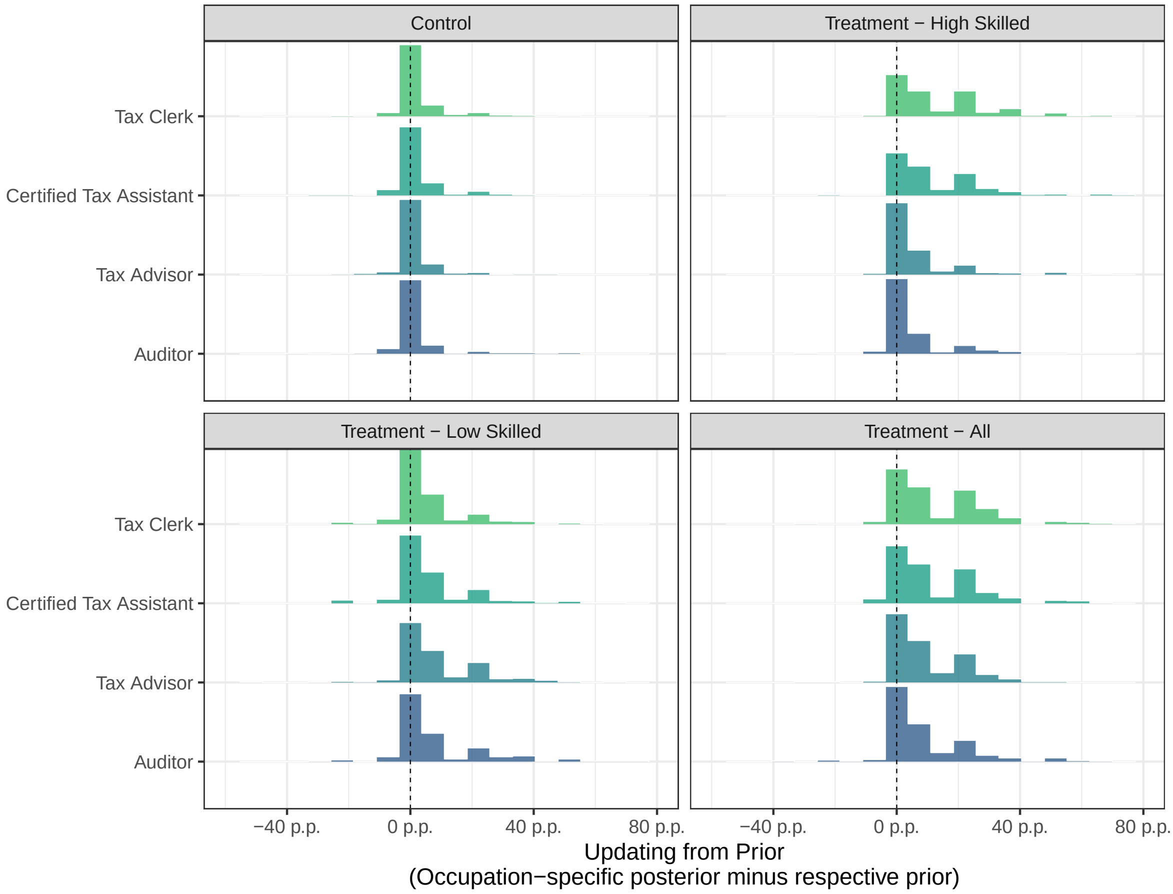
To examine how tax firms revise their beliefs about task automatability in response to new information, we compare prior and posterior beliefs across treatment and control groups.

Figure 6 plots the average belief shift (posterior minus prior) by occupation and treatment arm. As expected, belief changes in the control group are minimal and centered around zero, suggesting that expectations remain stable in the absence of new information. In contrast, all three treatment arms exhibit clear upward revisions, particularly for lower-skilled occupations such as Tax Clerks and Certified Tax Assistants. This indicates that structured information interventions prompt respondents to reassess the automation risks of specific job roles.

As expected, respondents in the control group exhibit little to no updating with the entire histogram centered around 0, suggesting that beliefs remain stable in the absence of new information. In contrast, all three treatment arms show clear evidence of belief revision. On average, respondents update their beliefs upward, consistent with receiving a positive signal about automation risk.

Importantly, belief updating is most pronounced for lower-skilled occupations such as Tax Clerks and Certified Tax Assistants, while higher-skilled roles like Tax Advisors and Auditors show smaller shifts. Interestingly, belief changes are not limited to the occupation specifically mentioned in the information treatment. For example, respondents receiving information about tax Avdisors and Auditors also revise their beliefs about Tax Clerks or Certified Tax Assistants upward, suggesting cross-occupational learning. This pattern is consistent with respondents generalizing the automation message to adjacent roles, indicating a broader reinterpretation of occupational risk once exposed to the signal.

Figure 6: Belief Updating by Occupation and Treatment Arm



Note: Each panel shows posterior minus prior beliefs about the share of automatable tasks, broken down by occupation and treatment arm. Shifts to the right reflect belief updating toward higher perceived automatability.
Source: German Business Panel Tax Advisor Survey 2025

Our empirical strategy uses the information provision experiment to identify the causal effect of automatability news on firm perceptions, expectations, and plans. In Appendix C we show in detail how the causal effect is identified in a 2SLS framework with Bayesian belief updating and implications for the first stage and second-stage regression models.

Bayesian Learning Framework for Belief Updating We formalize the belief updating process using a Bayesian learning framework in which respondents integrate new information from the treatment with their prior beliefs about the automability of specific occupations (e.g. Coibion et al., 2025). Since we elicited detailed priors and posteriors for four occupations, we estimate a fully saturated model that allows belief updating to differ by occupation and treatment arm:

$$\text{posterior}_{io} = \alpha_o + \beta_o \cdot \text{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \text{prior}_{io}) + \varepsilon_{io}, \qquad (1)$$

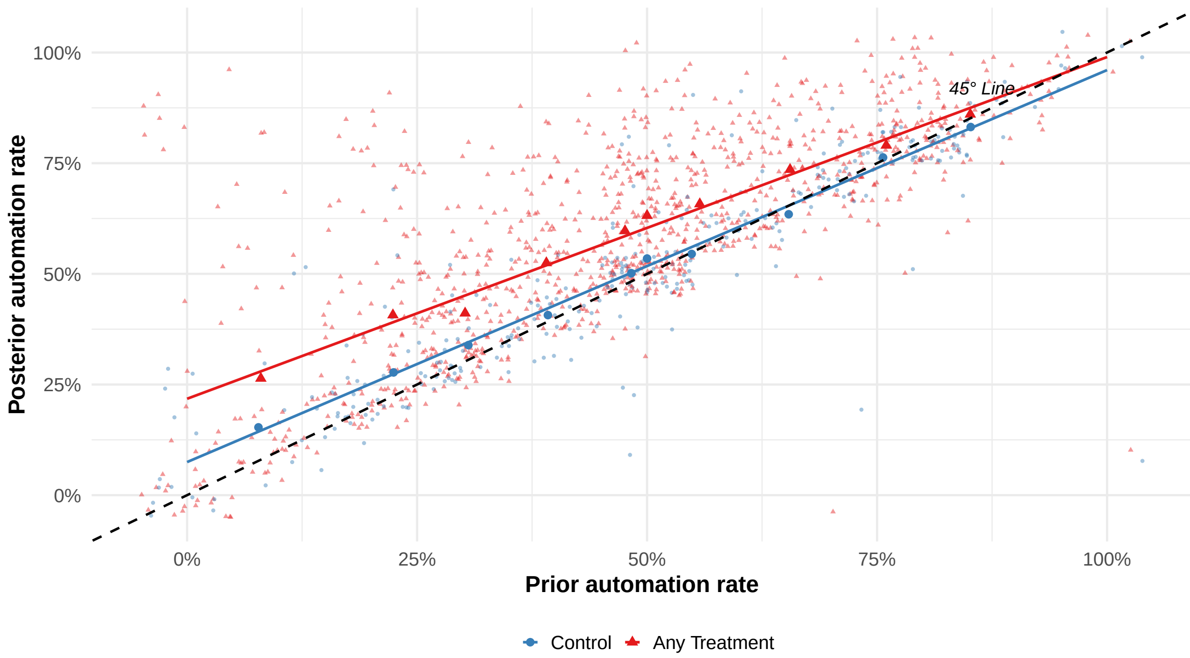
where i indexes respondents, $o \in \{\text{Clerk, Assistant, Advisor, Auditor}\}$ denotes the occupation, and $j \in \{\text{Low-skill, High-skill, Combined}\}$ indexes the three treatment arms. The dummy variable D_{ij} equals one if respondent i received treatment j, and zero otherwise. This specification allows both the direct treatment effect (δ_{oj}) and the slope with respect to prior beliefs (γ_{oj}) to vary by occupation and treatment. γ_{oj} indicates whether individuals with stronger priors discount new information more heavily, the coefficient β_o captures overall persistence in beliefs in the control group. The framework allows for heterogeneous learning in line with Bayesian updating, where individuals rationally weigh new information relative to their existing beliefs depending on its perceived novelty or informativeness (Sims, 2003). A key implication of these results is that γ serves as a measure of the learning rate when $\beta \approx 1$. Since β is close to unity, prior beliefs are not updated and equal the posterior beliefs.

Scatterplots showing Bayesian Updating We first visually examine whether belief updating follows this Bayesian learning process, whereby respondents combine their prior beliefs with the signal received in the information treatment, starting with some simple scatterplot to present the main intuition. Figure 7 plots individual-level prior and posterior beliefs for Tax Clerks, with separate trends for the control and treatment groups.

The control group (blue dots) largely adheres to the 45 degree line, suggesting that in the absence of new information, respondents' beliefs remain stable. In contrast, those being in any of the four treatment arm and receiving an information treatment (red triangles) tend to shift upward, suggesting that structured information interventions lead employers to revise upward their beliefs of how automatable the task of certified tax assistants are.

Similar adjustments can also be observed across other tax occupations, as shown in Figure A.5 in the Appendix. This adjustment is most pronounced for lower-skilled roles, such as tax clerks and certified tax assistants, while belief updating is weaker for higher-skilled roles, such as tax advisors and auditors. However, the extent of these adjustments varies systematically with the strength of prior beliefs.

Figure 7: Prior and Posterior Beliefs for Certified Tax Clerks



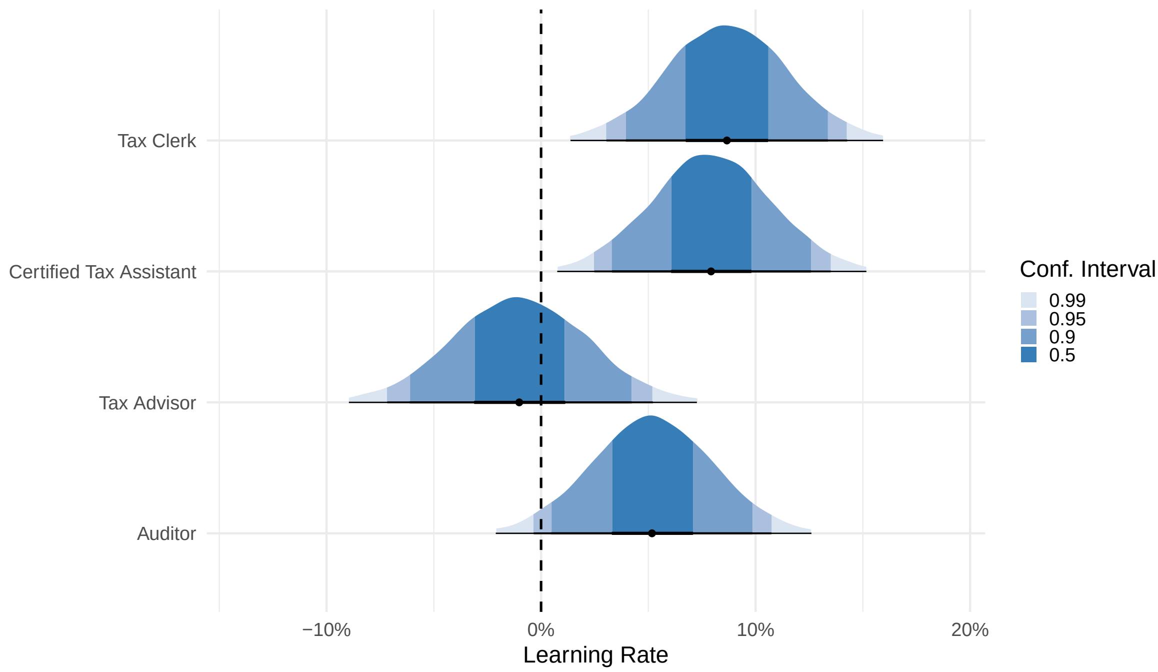
Note: This figure illustrates belief updating about automation rates based on regression equation (1) for Tax Clerks. The horizontal axis represents respondents' prior beliefs, and the vertical axis shows their posterior beliefs about automation rates. Light blue dots represent individual values in the control group, while red triangles denote those in any treatment arm. Larger, darker markers indicate averages for 10 quantile bins within each group. The dashed 45 degree line represents no belief updating.

Source: German Business Panel Tax Advisor Survey 2025

Empirical Evidence of Belief Adjustment Next, we present results for the specification from equation 1 for all four occupations in Table A.2 in the Appendix. The information treatments prompt substantial belief updating among employers regarding the automatability of tax occupations. Across all models, the coefficient on prior beliefs (β_o) is close to one, indicating that, in the absence of new information, employers largely rely on their existing expectations when forming posterior beliefs about automation risk. However, the negative and statistically significant interaction terms (γ_{oj}) for Tax Clerks and Tax Assistants reveal that, when exposed to the information treatment, employers discount their prior beliefs more heavily and are more likely to revise their expectations for these lower-skilled roles. For Tax Advisors, belief updating appears limited, as reflected in small and statistically insignificant interaction terms across all treatment arms. For Auditors, by contrast, we find a negative and statistically significant interaction effects indicating information updating.

Learning Rates and Responsiveness to Information The results that employers are more open to updating their views about automation risk for lower-skilled positions, while remaining more anchored in their priors for higher-skilled roles, potentially reflects stronger convictions or perceived job complexity at higher levels.

Figure 8: Learning rates



Note: This figure presents the estimated learning rates for different occupations in the tax advisory and auditing sector. Learning rates are derived from a Bayesian updating framework based on regression equation (1), where belief shifts in automation potential are modeled as a function of prior expectations and information treatment exposure. The individual γ_o parameters from equation (1) shown in Figure A.5 are aggregated with the delta method using the proportions of the treatment arm (roughly 0.25 for each arm). The density plots visualize the distribution of estimated learning rates across occupations, with shading indicating different confidence intervals (50%, 90%, 95%, and 99%). A higher learning rate suggests greater responsiveness to new information about automation rates.
Source: German Business Panel Tax Advisor Survey 2025

Figure 8 visualizes the overall learning rate for each occupation, derived by aggregating the interaction coefficients across treatment arms using the delta method, and drawing from the estimated distribution to visualize confidence regions. The Figure shows that learning rates are highest for Tax Clerks and Certified Tax Assistants, where firms are most responsive to new information, and lowest for Tax Advisors, where beliefs remain largely unchanged. The confidence intervals confirm that belief updating is statistically significant for the lower-skilled roles, marginally significant for auditors, while the learning rate for Tax Advisors is not distinguishable from zero, highlighting the limited effect of the information treatment on beliefs about this occupation.[6]

The OLS regression in Table A.2 in the Appendix shows also that the treatment increases respondents beliefs about the automatability of their own job. Since respondents underestimate the share of automatable tasks in their job, it implies that respondents update their beliefs in line with the information provided. When being informed about the automation probability, the belief about automation rate shifts.

3.2 Employment and Revenue Expectations

While the results above demonstrate that employers systematically revise their beliefs about the automatability of their workforce in response to new information, shifting expectations about automation does not necessarily translate into changes in firm behavior. Whether belief updates influence concrete decisions, such as hiring, wage setting, or investment strategies, remains an open question.

Instrumenting Automation Beliefs To identify the causal effect of automation beliefs on these firm-level outcomes, we exploit the experimental variation from the information treatment as an instrument. Specifically, we estimate a two-stage least squares (2SLS) model, where posterior beliefs about automation rates, endogenously determined by priors and treatment assignment, serve as instrumented predictors of firm behavior. This approach allows us to isolate the exogenous variation in belief shifts and rule out potential confounders that could simultaneously affect both expectations and firm decisions. The second-stage regression is specified as follows:

$$Y_i = \beta_0 + \sum_o \beta_{o1} \widehat{\text{z}}_{io} + \mathbf{X}_i' \gamma + \eta_i, \tag{2}$$

where Y_i denotes the outcome of interest for firm i (e.g., revenue expectations or employment plans), $\widehat{\text{z}}_{io}$ are the fitted values from the first-stage regressions for each occupation o, and $\mathbf{X}_i$ is a vector of predetermined firm and individual-level control variables. Since the experiment achieved good balance in observable characteristics across treatment arms due to randomization, results stay virtually unchanged if no controls are included.

Because, the information treatment generates joint variation in beliefs across all four occupations, it is not meaningful to interpret the β_{o1} coefficients as ceteris paribus effects. Instead, we summarize the overall impact of belief updating by calculating the impact at

[6] The raw first stage estimates are shown in Table A.2 in the Appendix.

an average belief updating for all occupations in the combined treatment using a linear combination of the second-stage coefficients:

$$\sum_{o=1}^{4} \hat{\beta}_{o1} \cdot \overline{\text{Updating}}_{o,\text{Treatment-Combined}}. \tag{3}$$

To account for joint estimation uncertainty, we apply the delta method to derive standard errors and confidence intervals for this linear combination. The mean belief shift induced by the combined information treatment is substantial across all four occupations. The mean belief shift induced by the combined information treatment is substantial across all four occupations: on average, beliefs about the automatable task share increased by 13.1 for tax clerks, 12.2 for certified tax assistants, 9.1 percentage points for tax advisors, and 9.3 for auditors.[7]

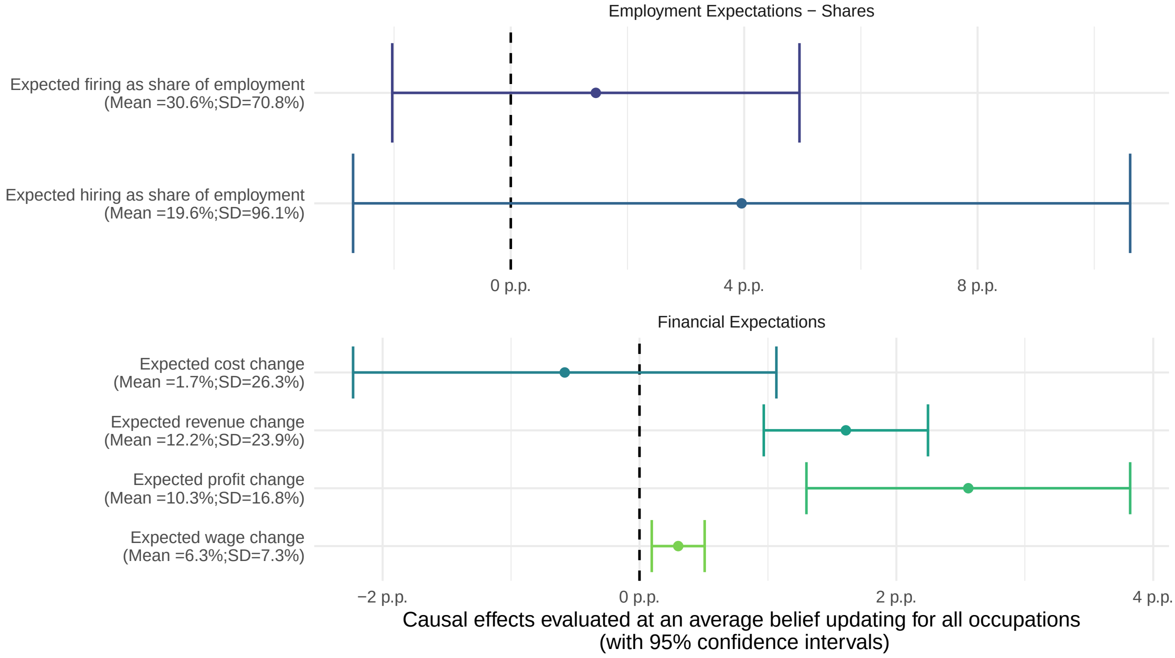
This approach offers two key advantages. First, it yields a single, interpretable quantity that captures the expected effect of the information treatment at representative levels of belief updating. Second, it avoids problematic ceteris paribus interpretations that arise when individual posteriors are treated as if they could vary independently, despite being jointly determined by the treatment.

3.3 Employment and Revenue Expectations

The coefficient plot in Figure 9 illustrates the effects of belief updating about automation on firm-level employment and financial expectations. Estimates are derived from second-stage IV regressions using updated automation beliefs instrumented by our randomized information intervention.

[7] An alternative strategy would be to use the standard deviation of posterior beliefs within each treatment arm as a proxy for information diffusion or belief dispersion and to aggregate effects in a similar way. However, we take a conservative approach and summarize average effects based on mean belief updating. In our data, standard deviations in posteriors are typically about twice as large as the mean shift, so relying on averages typically leads to lower but more realistic treatment effect ranges.

Figure 9: Coefficient plot for main outcomes



Note: This figure shows the causal effects of the information treatment. We compute the aggregate causal effect as a linear combination of second-stage coefficients from regression (2) on the posterior belief weighted by the average belief shift in the treatment group for all four occupations (see equation (3)). Means and standard deviations of the outcomes are reported in the labels on the vertical axis. Error bars represent 95% confidence intervals, with standard errors calculated via the delta method to account for the joint estimation. The outcome variables are hiring, firing, and revenue as well as cost expectations.

Source: German Business Panel Tax Advisor Survey 2025

In the upper panel (Employment Expectations), we see that the effects of updated automation beliefs on both expected firing and expected hiring as a share of employment are statistically indistinguishable from zero. The estimated coefficients are small, and the confidence intervals span both positive and negative values. The baseline for expected firing is 30.6% (SD: 70.8%) and for expected hiring is 19.6% (SD: 96.1%). It is important to note that the average firm in the sample is small, with fewer than 10 employees, so these large percentage shares reflect relatively small absolute adjustments planned over the next three years. Compared to this substantial underlying variation, the treatment effects of the information intervention on employment plans are negligible.

The lower panel (Financial Expectations) shows the effects of updated automation beliefs on firms' cost, revenue, profit, and wage expectations. The estimated effect on expected cost change is negative and statistically insignificant (point estimate = −0.6 percentage points, p = 0.49), suggesting that firms do not anticipate significant cost increases due to AI. By contrast, there are statistically significant positive effects on both expected revenue and profit: the intervention increases expected revenue by 1.6 percentage points ($p < 0.001$) and expected profit by 2.6 percentage points ($p < 0.001$) over the baseline means. Although these magnitudes may appear modest, they are notable relative to the mean and standard deviation of the respective outcomes, especially for profits.

Interestingly, the effect on expected wage change is also positive and statistically significant, but much smaller in magnitude (just 0.3 percentage points, $p = 0.004$). This effect is minor compared to the baseline mean of 6.3% (and standard deviation of 7.3%), implying that firms do not plan to pass on the anticipated financial gains from automation to employees in the form of higher wages, at least not on a comparable scale. At the same time, the narrow confidence interval for wage expectations reinforces the precision of this null finding.

These findings align with the research on rent-sharing, that shows that firms often do not share productivity gains with employees through higher wages, especially when such gains are derived from automation or technological advancements. For instance, Kline et al. (2019) found that workers capture only a fraction of the surplus generated by patents, with significant disparities based on tenure and position within the firm. Similarly, Cho and Krueger (2022) observed that rent-sharing within firms is uneven, favoring higher-earning employees.[8]

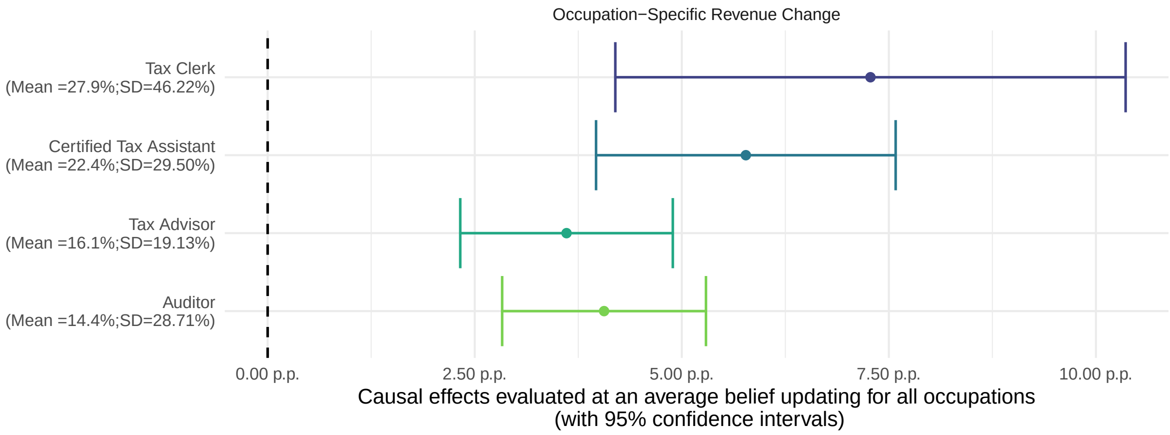
Moreover, these findings are consistent with recent evidence from Denmark. Humlum and Vestergaard (2025) study chatbot adoption among workers in AI-exposed occupations using linked survey and administrative data. Despite widespread usage, time savings, and firm-level encouragement, they find no measurable changes in hours worked or earnings, with precise confidence intervals that rule out even modest effects. Only a small share of the productivity gains (estimated at 3-7%) is passed through to wages. Our results echo this pattern: while firms revise their beliefs about automation and anticipate financial benefits, they do not expect to share these gains proportionally with workers. This highlights how belief formation and managerial expectations shape the early-stage impact of AI.

[8] This might be in part because the wage schedule for most tax occupations is fixed. This is in line with research by Franceschelli et al. (2010), who show that productivity gains under performance pay schemes translate more directly into higher wages compared to fixed-wage schemes, where productivity improvements have a more limited effect on employee compensation, even when both types of workers achieve similar productivity increases.

3.4 Occupation-Specific Revenue Expectations

To further examine how belief updating affects firms' economic expectations, Figure 10 breaks down the expected revenue growth attributed to automation-induced belief updates by different tax-related occupations. We again use the same IV strategy and present the aggregated effects for average belief updating.

Figure 10: Coefficient plot for occupation-specific hourly revenues



Note: This figure shows the causal effects of the information treatment. We compute the aggregate causal effect as a linear combination of second-stage coefficients from regression (2) on the posterior belief weighted by the average belief shift in the treatment group for all four occupations (see equation (3)). Means and standard deviations of the outcomes are reported in the labels on the vertical axis. Error bars represent 95% confidence intervals, with standard errors calculated via the delta method to account for the joint estimation. The outcome variables are perceived occupation-specific revenues per hour.
Source: German Business Panel Tax Advisor Survey 2025

The estimates reveal that across all occupations, higher posterior beliefs about automatability are associated with significantly higher expected revenue growth. This suggests that firms anticipating greater automation in these roles expect efficiency gains to translate into revenue increases. However, the magnitude of this effect varies across occupations.

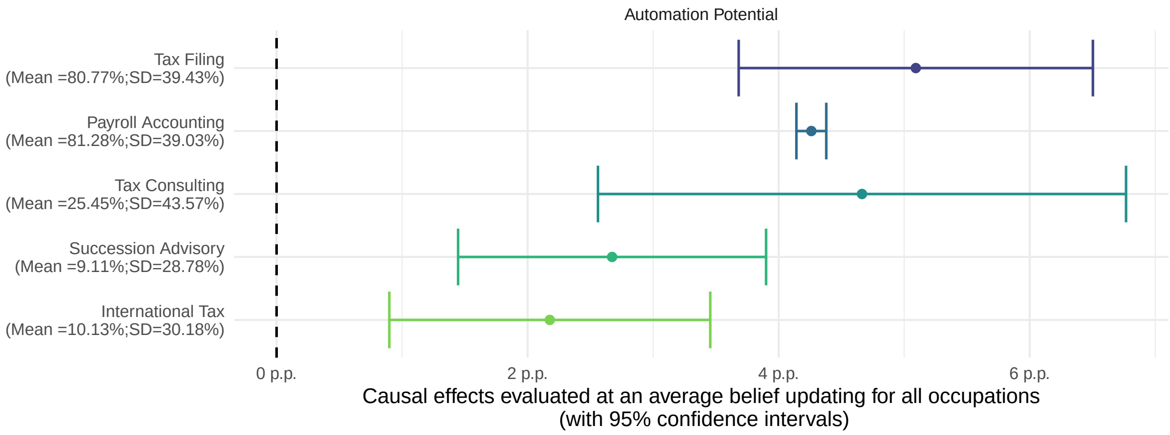
The largest estimated effect appears for Tax Clerks, where a representative treatment-induced update in automation beliefs is associated with an expected increase in hourly revenues of 7.3 percentage points (95% CI: 4.2 to 10.4). Certified Tax Assistants exhibit a somewhat smaller effect at 5.8 percentage points (95% CI: 4.0 to 7.6). For higher-skilled roles, the estimated effects are more modest, with expected increases of 3.6 (95% CI: 2.3 to 4.9) and 4.1 (95% CI: 2.8 to 5.3) percentage points for Tax Advisors and Auditors, respectively. However, the confidence intervals for these estimates overlap, particularly between the two lower-skilled and two higher-skilled occupations, indicating that the differences in point estimates may not be statistically significant. Yet, for the high-skilled occupations for which we observed lower learning rates, less productivity increases are expected.

3.5 Automation Potential and New Tasks

The results thus far have demonstrated that firms systematically update their future plans when exposed to new information. The evidence presented in Figure 11 reveals how the overall information shock translates into perceived automation potential at the task level.

Here, the dependent variables are binary indicators equal to one if a respondent believes that a given task, such as tax filing, payroll accounting, tax consulting, succession advisory, or international tax advisory, has automation potential.

Figure 11: Coefficient plot for automation potential



Note: This figure shows the causal effects of the information treatment. We compute the aggregate causal effect as a linear combination of second-stage coefficients from regression (2) on the posterior belief weighted by the average belief shift in the treatment group for all four occupations (see equation (3)). Means and standard deviations of the outcomes are reported in the labels on the vertical axis. Error bars represent 95% confidence intervals, with standard errors calculated via the delta method to account for the joint estimation. The outcome variables are perceived automation potential at the task level. Each point shows the change in probability that respondents assign automation potential to a specific task (e.g., tax filing, payroll accounting, tax consulting, succession advisory, or international tax advisory)
Source: German Business Panel Tax Advisor Survey 2025

Consistent with our earlier findings, respondents exposed to the information treatment report significantly higher automation potential for lower-skilled tasks, particularly those traditionally performed by Tax Clerks and Certified Tax Assistants such as like Tax Filing and Payroll Accounting.

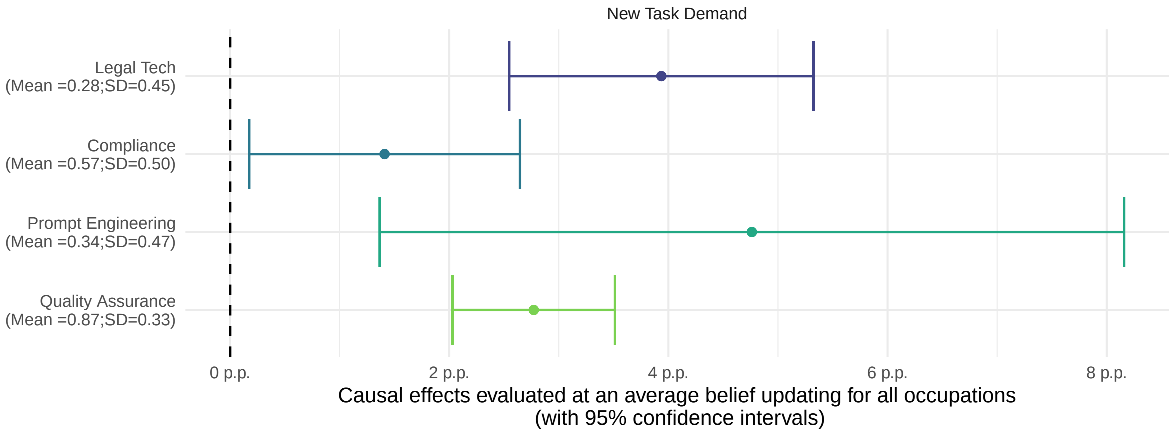
Treated respondents report significantly higher probabilities that routine tasks such as tax filing and payroll accounting can be automated. The estimated increases for these tasks are around four to five percentage points, indicating that the information treatment leads to a marked shift in perceptions of automation potential in the most routine-intensive areas. For more complex or advisory tasks like tax consulting, succession advisory, and international tax advisory, the effects are smaller and estimated less precisely, albeit still significantly positive. This pattern demonstrates that firms' beliefs about which aspects of their work are automatable are particularly responsive in routine, lower-skilled domains.

However, the fact that treated respondents revise their beliefs even for high-skilled tasks suggests that AI-based tools and automation solutions are beginning to shape expectations beyond purely routine work. While automation expectations remain strongest for procedural and compliance-related work, firms do not entirely discount the potential for AI-driven automation even in high-skilled advisory roles.

Beyond revising their expectations about the automation potential of existing tasks, respondents also anticipate the emergence of new tasks as a consequence of automation. This raises the question of how firms expect job roles to evolve in response to automation and whether they foresee a net displacement of tasks or an expansion into new responsibilities that complement AI-driven workflows.

To explore this, Figure 12 highlights anticipated changes in demand for new tasks emerging alongside automation. Here, the dependent variables are binary indicators for whether respondents expect Legal Tech, Compliance, Prompt Engineering, or Quality Assurance to become relevant as part of their evolving job responsibilities.

Figure 12: Coefficient plot for new tasks



Note: This figure shows the causal effects of the information treatment. We compute the aggregate causal effect as a linear combination of second-stage coefficients from regression (2) on the posterior belief weighted by the average belief shift in the treatment group for all four occupations (see equation (3)). Means and standard deviations of the outcomes are reported in the labels on the vertical axis. Error bars represent 95% confidence intervals, with standard errors calculated via the delta method to account for the joint estimation. The outcome variables are expectations for the emergence of new tasks, including the probability that respondents report increased relevance of Legal Tech, Compliance, Prompt Engineering, and Quality Assurance.
Source: German Business Panel Tax Advisor Survey 2025

The results reveal that higher automation beliefs significantly increase the likelihood of respondents considering new tasks relevant, though the effect sizes vary across task types.

The largest effects are observed for Prompt Engineering, involving direct interaction and optimization of AI outputs, and Legal Tech, with estimated increases of roughly 4.8 and 3.9 percentage points, respectively. While still a relatively new concept in professional tax work, this suggests that some tax professionals are beginning to anticipate the growing role of AI interaction and optimization as part of their job, reflecting broader labor market trends where demand for AI-related skills has increased across diverse occupations, often accompanied by wage premiums (Alekseeva et al., 2021).

Quality Assurance also sees a significant positive effect of 2.8 percentage points, despite already being regarded as highly important even for individuals who do not update their priors (with 87% of the respondents reporting that it is important).

For Compliance, the effect is smaller, about 1.4 percentage points, but still statistically significant. This pattern suggests that respondents foresee a shift not just toward the automation of existing, routine work, but also toward an expansion of new, tech-oriented or oversight-oriented responsibilities. The means reported in the Figure labels further illustrate that while some of these tasks (like Quality Assurance and Compliance) are already widely relevant, others (such as Legal Tech and Prompt Engineering) are poised for significant growth in importance.

These differences underscore varying degrees of perceived complementarity between AI and human expertise. Legal Tech and Compliance are seen as domains likely to require upskilling in legal automation and regulatory monitoring, while Prompt Engineering signals an early recognition of AI interaction skills as a novel job component. Quality Assurance, by contrast, remains a core responsibility, likely shifting focus toward mitigating AI errors rather than creating entirely new workflows.

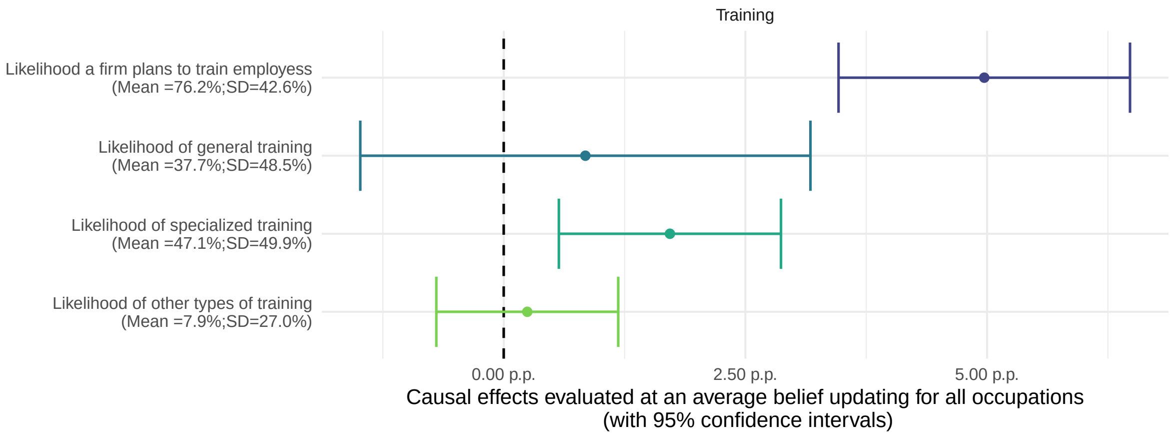
Rather than replacing professionals, automation appears to be driving a transition toward augmented work, where human oversight and AI-driven processes increasingly coexist. This aligns with the perspective that automation often complements, rather than substitutes for, human labor-creating new tasks where human expertise remains critical (e.g., Acemoglu and Restrepo, 2019; Brynjolfsson and McAfee, 2014). As Acemoglu and Restrepo (2019) argue, the net impact of automation on labor demand hinges on the balance between displacement of existing tasks and the emergence of novel roles that leverage human comparative advantage. Similarly, Brynjolfsson and McAfee (2014) emphasize that while routine tasks are automated, new roles arise requiring advanced cognitive and interactive skills, reinforcing the idea that technology reshapes job content rather than simply eliminating work.

3.6 Employer-provided training

Automation is widely seen as a catalyst for organizational change, prompting firms to adapt not only their processes but also their approach to workforce development. Previous studies have shown that automation risk can drive both upskilling and changes in job mobility. For instance, Sotiris et al. (2019) argue that workers confronted with automation either move into lower-paid, less automatable occupations or acquire new skills to complement technology and access higher-paid roles. Similarly, Lergetporer et al. (2023) find that providing information about automation risks increases employees' willingness to participate in further training, particularly among those in highly automatable occupations, with effects of around five percentage points. However, they also highlight that misperceptions about which tasks are truly automatable may explain why participation in training remains low among less-skilled groups. The importance of task content is further underlined by Heßet al. (2019), who show that employees performing highly routine tasks participate in training less frequently than those in less routine jobs, and that, somewhat counterintuitively, those who use computers extensively report below-average training participation.

Building on this literature and our previous results that show that employers anticipate the emergence of new tasks (e.g. Legal Tech and Prompt Engineering) due to automation, we examine firms' plans for employee training (or upskilling) in response to the information intervention.

Figure 13: Effect of information treatment on planned training investments

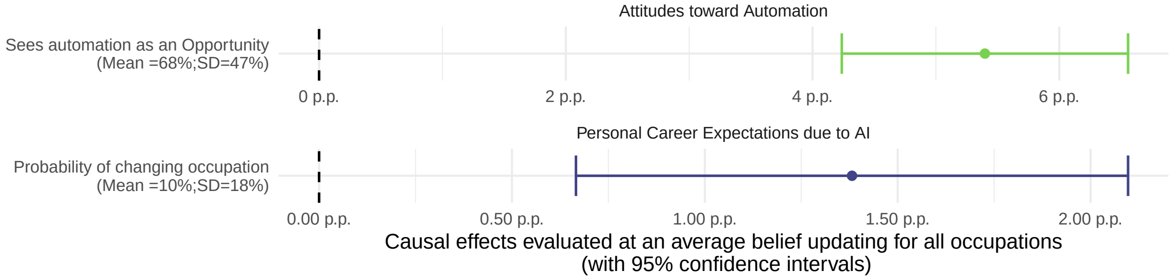


Note: This figure shows the causal effects of the information treatment. We compute the aggregate causal effect as a linear combination of second-stage coefficients from regression (2) on the posterior belief weighted by the average belief shift in the treatment group for all four occupations (see equation (3)). Means and standard deviations of the outcomes are reported in the labels on the vertical axis. Error bars represent 95% confidence intervals, with standard errors calculated via the delta method to account for the joint estimation. The outcome variables are the likelihoods that firms plan automation-related training investments.
Source: German Business Panel Tax Advisor Survey 2025

As shown in Figure 13, exposure to automation information significantly increases the probability that firms plan further training for their staff, raising the likelihood by about 5 percentage points from an already high baseline of 76%. This effect is concentrated in specialized training, such as technical courses or certifications, which increases by about 1.7 percentage points and is statistically significant. By contrast, the treatment does not meaningfully affect plans for general training (e.g., part-time study) or other types of training, where baseline levels are much lower and effects are not statistically significant.

Similarly, our treatment impacts attitudes towards automation. To this end, Figure 14 complements our earlier firm-level results by documenting how the information shock reshapes individual mind-sets and planned behaviour.

Figure 14: Effect of Automation Information on Automation Attitudes, and Career Plans



Note: The outcome variables are: (i) perceiving automation as an opportunity, and (ii) the self-assessed probability of changing occupation.
Source: German Business Panel Tax Advisor Survey 2025

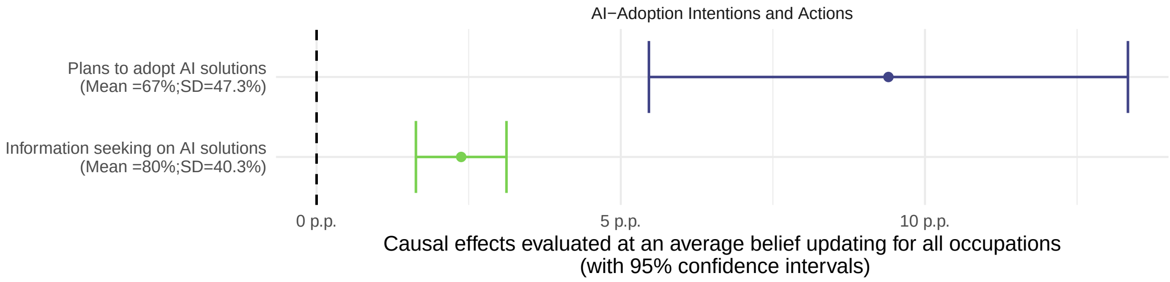
We use the probability of seeing automation as an opportunity as a measure of general sentiment. This figure rises by 5.4 p.p. (about 8% relative to its 68% mean). This shift is noteworthy in light of prior evidence from Germany suggesting that automation is predominantly perceived as a threat to employment (Arntz et al., 2022).

Finally, the treatment increases the self-reported likelihood of changing occupation by 1.4 p.p. on a 0-100% scale. Although modest in absolute terms, this is a 13% relative rise over the 10.4% baseline, suggesting that a minority of professionals begin to contemplate career moves once automation risks are made salient. The pattern dovetails with cross-country evidence that automation concerns spur skill-investment and career planning (Innocenti and Golin, 2022), yet it also shows that most respondents do not leap to drastic career changes; instead, they prefer upskilling and tool adoption within their current field.

3.7 Intentions and Actions

To quantify the extend to which intentions stated in the survey translate into real-world actions, we measure how the information provision experiment affects the plans to adopt AI solutions and information search choices about AI solutions. Figure 15 reports the results.

Figure 15: Effect of Automation Information on AI-Adoption Intentions and Actions



Note: The outcome variables are: (i) plans to adopt AI solutions, (ii) active information seeking about such tools within.
Source: German Business Panel Tax Advisor Survey 2025

For plans to adopt AI solutions we find large responses, which rise by 9.4 p.p. from a baseline mean of 66.5%. This corresponds to a 14% increase relative to the mean, underscoring that belief updating will translate into actual AI use for affected firms.

For a subset of individuals, who did not know tax-specific AI-tools, [9] we elicited whether they were interested to learn more about these tools and give a link to a description page to measure information seeking. For this group we find small, but significant, effect of 2.4 p.p.; the muted magnitude is consistent with a ceiling effect, given the already high baseline of 80%.

Our second test of how stated intentions correspond to choices uses data from the official job portal of the German Federal Employment Agency.

To validate the hiring intentions reported in our survey, we tracked participating firms on the official job advertisement portal of the German Federal Employment Agency. Using a fuzzy matching algorithm based on firm names, we identified job postings attributable to survey respondents. We then compared these postings to the hiring plans stated in the survey. As expected, only a small subset of firms with reported hiring plans had active listings on the public portal, likely reflecting the common use of informal recruitment channels or the hiring of interns, which are not typically advertised online. However, all firms with a posted job advertisement also reported corresponding hiring plans in the survey, indicating strong internal consistency. When job postings specified particular occupations, we were able to directly verify alignment with occupation-level hiring intentions stated by respondents. In all such cases, the occupations mentioned in the job ads (e.g., tax advisors, tax clerks, or certified tax assistants) matched those for which firms reported positive hiring plans. Notably, some ads combined multiple

[9] These are typically retrieval-augmented chatbots that accurately cite court-decisions and tax-laws.

occupations, most commonly tax clerks and certified tax assistants, within a single listing. The absence of reverse matches (i.e., survey-reported plans without corresponding ads) may reflect budgetary constraints, changes in staffing needs, or alternative recruitment strategies that prevented some intended hires from materializing as public job postings.

3.8 Robustness

In Appendix B we compare 2SLS estimates with corresponding reduced form estimates. In Appendix C we show the conditions under which the Bayesian-updating model, the reduced-form regressions identifies the same causal estimates as 2SLS.

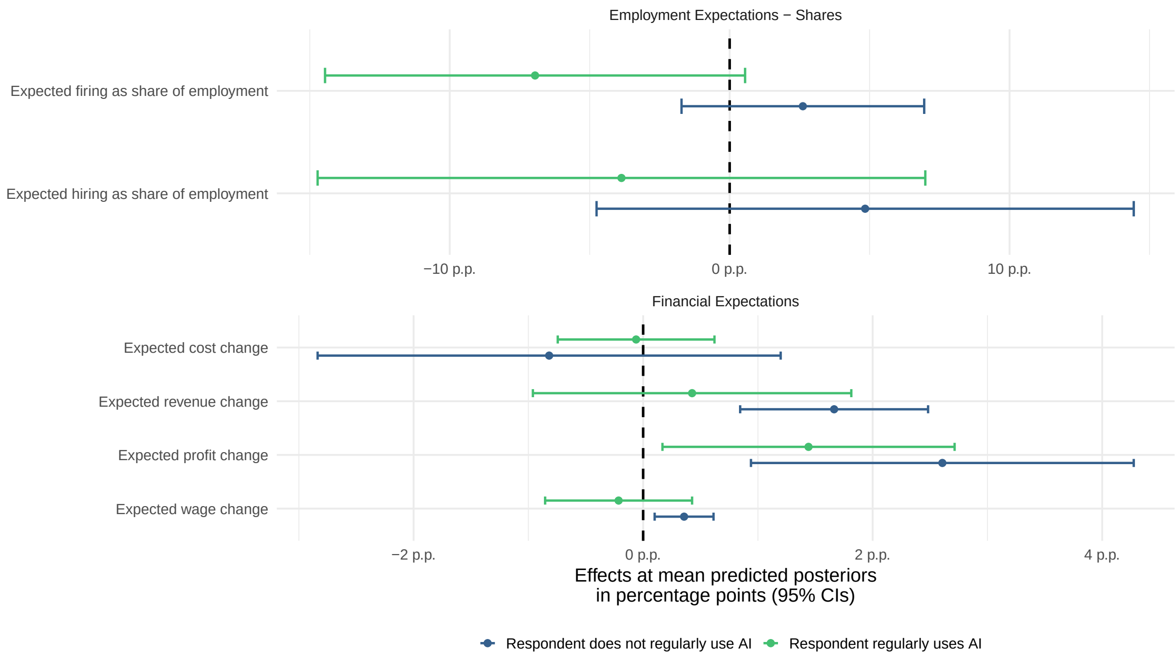
Across all outcomes, the reduced-form estimates line up closely with the 2SLS estimates that scale by the treatment-induced change in beliefs. Both approaches show essentially no effect on expected hiring or firing, but positive effects on expected revenue and profits and a very small, precisely estimated effect on wages when evaluated at the sample-average belief update. By occupation, both estimators imply larger expected revenue gains where tasks are more routine (Tax clerks, Certified assistants) and smaller, though still positive, for higher-skill roles (Tax advisors, Auditors). For task automation, they agree that belief updates raise the perceived automatability of routine tasks (tax filing, payroll) more than advisory tasks.

Taken together, the empirical results are in line with the theoretical restrictions and demonstrate robustness for both the reduced-form and 2SLS estimates in this setting.

3.9 Heterogeneity

To assess whether main effects of belief updating on revenue and employment plans differ across relevant margins, we re-estimate the aggregated causal effects separately by (i) respondents' regular use of generative AI, (ii) firm size (total employment above/below the median), and (iii) respondent age (above/below the median).

Figure 16: Effect heterogeneity by baseline AI use

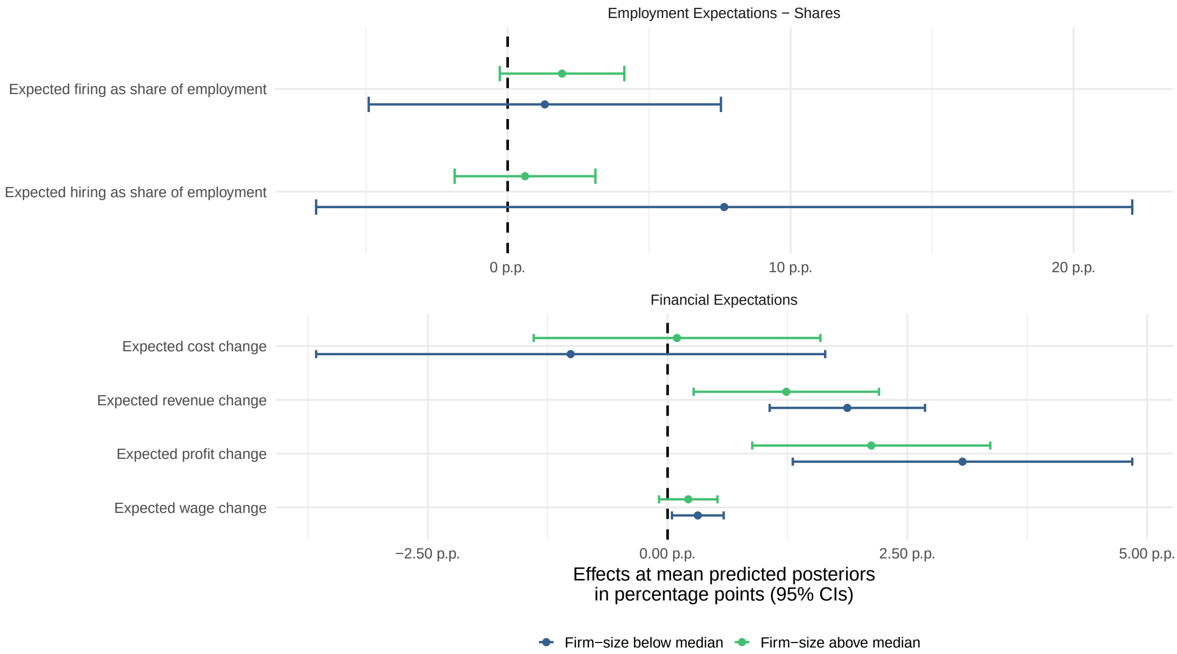


Note: This figure shows subgroup-specific causal effects of the information treatment. We compute the aggregate causal effect as a linear combination of second-stage coefficients from regression (2) on the posterior belief weighted by the subgroup-specific average belief shift in the treatment group for all four occupations (see equation (3)). Error bars represent 95% confidence intervals, with standard errors calculated via the delta method to account for the joint estimation. Outcome variables are employment and financial expectations, separately for respondents who (do not) regularly use AI.
Source: German Business Panel Tax Advisor Survey 2025

Figure 16 shows that respondents who do *not* yet use AI regularly exhibit larger point estimates for forward-looking business expectations. This is consistent with the signal being more salient for less informed individuals. However, confidence intervals for both regular and non-regular users overlap substantially, indicating that most differences are not statistically significant.

Employment expectations, both hiring and firing shares, remain close to zero in both groups. If anything, point estimates for regular AI users are slightly negative, suggesting that early adopters anticipate internal efficiency gains rather than near-term changes in staffing. Overall, while not statistically significant, the pattern is suggestive of catch-up effects: firms that have not yet integrated AI perceive greater scope for productivity improvements when prompted by new information.

Figure 17: Effect heterogeneity by firm size

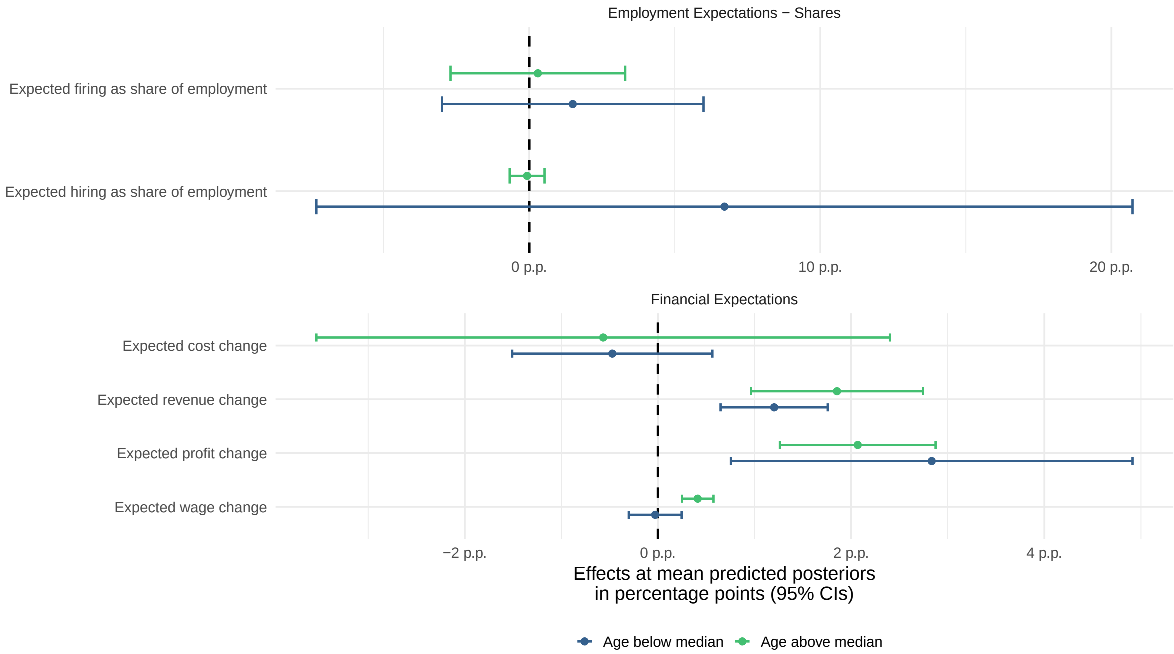


Note: This figure shows subgroup-specific causal effects of the information treatment. We compute the aggregate causal effect as a linear combination of second-stage coefficients from regression (2) on the posterior belief weighted by the subgroup-specific average belief shift in the treatment group for all four occupations (see equation (3)). Error bars represent 95% confidence intervals, with standard errors calculated via the delta method to account for the joint estimation. Outcome variables are employment and financial expectations, separately for firms below and above the median number of employees.

Source: German Business Panel Tax Advisor Survey 2025

Figure 17 shows broadly similar effects of belief updating for small and large firms. In both groups, higher automation beliefs translate into higher expected revenue and profits, and confidence intervals overlap substantially, indicating that the between-group differences are not statistically distinguishable. Only smaller firms display a statistically significant within-group wage effect (+0.32 p.p.), but the wage coefficients themselves are also not significantly different from each other. Overall, the data are consistent with positive financial expectations across the size distribution rather than sharply divergent responses.

Figure 18: Effect heterogeneity by respondent age



Note: This figure shows subgroup-specific causal effects of the information treatment. We compute the aggregate causal effect as a linear combination of second-stage coefficients from regression (2) on the posterior belief weighted by the subgroup-specific average belief shift in the treatment group for all four occupations (see equation (3)). Error bars represent 95% confidence intervals, with standard errors calculated via the delta method to account for the joint estimation. Outcome variables are employment and financial expectations, separately for respondents below and above the median age. *Source:* German Business Panel Tax Advisor Survey 2025

Figure 18 likewise reveals similar revenue and profit effects for younger and older respondents. The only clear between-group contrast concerns wages: older respondents anticipate a modest but statistically significant wage increase (+0.41 p.p.), whereas the younger group's point estimate is near zero. This is the only difference between the two age-groups that borders statistical significance.

Taken together, our heterogeneity analyses reveal a remarkably consistent pattern: the effects of automation belief updating on firms' employment and revenue expectations are largely uniform across key subgroups. Whether we split the sample by baseline AI adoption, firm size, or respondent age, the main results remain robust-belief shifts translate into improved financial outlooks but do not trigger immediate changes in hiring or firing plans. While there are small differences in magnitude, particularly with less regular AI users or older respondents, these are neither substantial nor statistically significant for most outcomes.

4 Conclusions

Our findings reveal several novel insights into how tax advisory and auditing firms perceive and respond to automation trends. First, we observe a significant gap between initial employer beliefs and expert assessments regarding automation potential. While firms tend to underestimate automation risks, our information intervention successfully prompts belief updating, particularly for lower-skilled occupations like tax clerks and certified tax assistants. For higher-skilled roles such as tax advisors and auditors, belief adjustments are more limited, suggesting that firms perceive greater barriers to automation at the top of the professional hierarchy.

Despite updating their beliefs about automation, firms do not immediately revise their hiring or firing plans, indicating that automation-induced workforce reductions are not a primary concern in the near term. However, firms that update their automation expectations anticipate higher revenue and profit growth, consistent with the notion that efficiency gains from automation may enhance firm performance rather than lead to immediate labor displacement. Interestingly, while firms foresee increased costs-potentially due to investment in new technologies or upskilling initiatives-wage expectations remain largely unchanged, implying that anticipated productivity gains are not expected to translate into higher employee compensation in the short run.

Moreover, our results highlight that automation is not merely perceived as a labor-replacing force but as a driver of job transformation. Firms exposed to updated automation information expect new tasks to emerge, particularly in areas like legal tech, compliance, and AI interaction roles such as prompt engineering. This suggests that while automation reshapes job content, it also creates opportunities for skill development and specialization rather than rendering professional roles obsolete.

These findings contribute to the broader economic literature on automation and labor markets in three key ways. First, they extend existing research beyond manufacturing and manual labor-intensive industries, showing how generative AI might influence a broad spectrum of white-collar occupations. Second, by taking an employer-centered perspective, our study captures anticipatory responses to automation before they materialize as observable labor market outcomes, offering a forward-looking view of technological adaptation. Finally, our results underscore the nuanced impact of automation on task composition, revealing that rather than reducing overall employment, automation may shift the skill demands of the workforce in ways that require continued investment in complementary human capital.

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A Additional Figures and Tables

Table A.1: Summary Statistics

Note: This table presents summary statistics for the full survey data including big firms with more than 150 employees or more than 10 Mio. Euro of revenue.
Source: German Business Panel Tax Advisor Survey 2025

Figure A.1: Expert Signal on Automatability by Occupation

(a) Tax Clerk

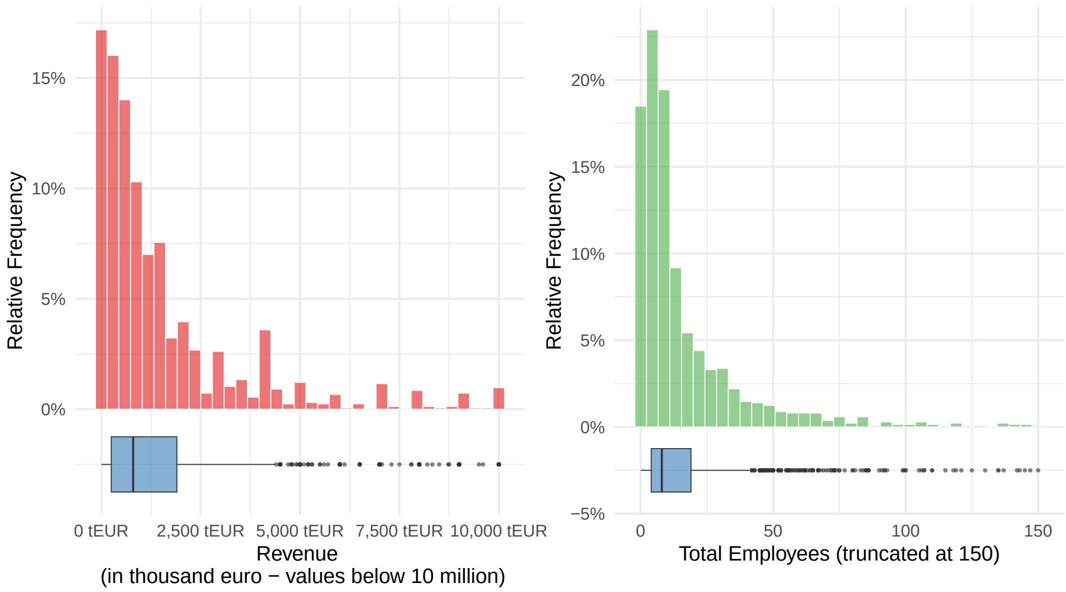
(b) Certified Tax Assistant

(c) Tax advisor

(d) Auditor

Note: This figure illustrates expert assessments of the automatability of tasks in selected tax-related occupations, based on data from Job-Futuromat, a tool provided by the German Federal Employment Agency. Each panel displays the share of tasks in the given occupation that can be automated with current technologies. The automatability estimates range from 57% for Auditors to 100% for Tax Clerks, indicating significant heterogeneity even within a single professional domain.
Source: Institute for Employment Research (IAB) https://job-futuromat.iab.de/en, 2025.

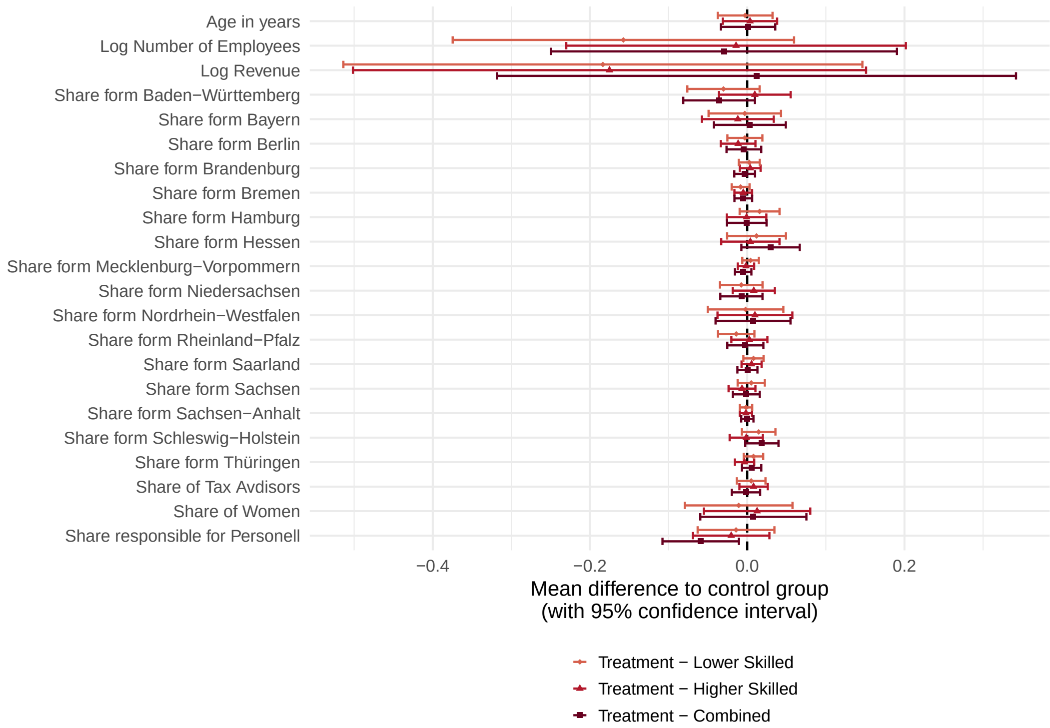
Figure A.2: Distribution of Firm Revenue and Employment



Note: This figure presents the distribution of firm revenue (left) and total employees (right) among survey respondents. The revenue distribution is displayed in thousand euros and excludes firms with revenues above 10 million euros. The employee distribution is truncated at 150 employees. Histograms illustrate the relative frequency of firms within each range, while boxplots provide additional insight into the spread and presence of outliers. The distributions confirm the presence of a highly skewed firm size distribution, with most firms being relatively small but a subset of large firms contributing to long right tails.

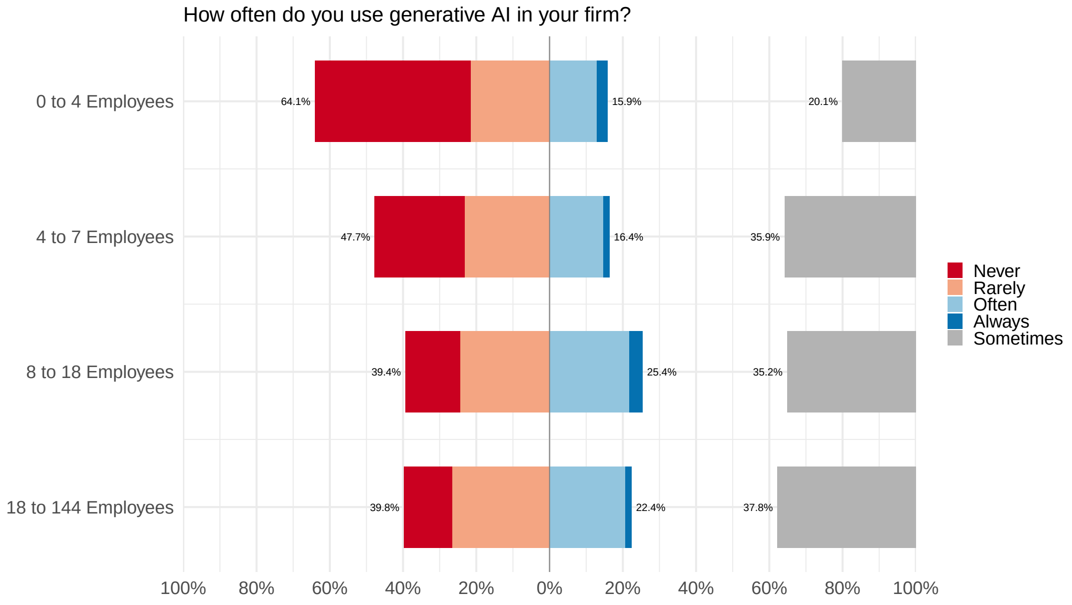
Source: German Business Panel Tax Advisor Survey 2025

Figure A.3: Covariate Balance across Treatment Arms



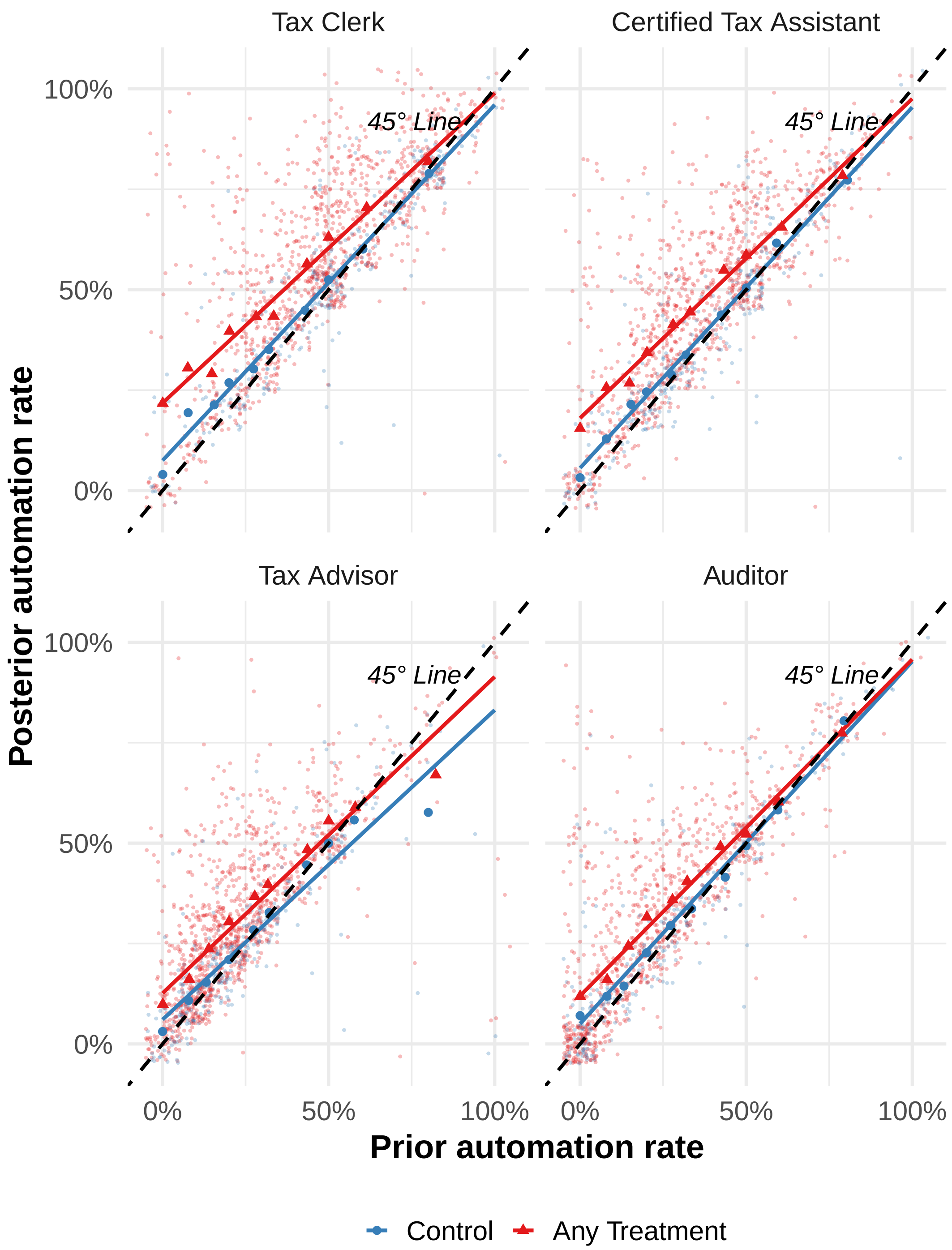
Note: This figure displays the mean differences in covariates between each treatment arm and the control group, with whiskers representing 95% confidence intervals. The results indicate no systematic imbalances across key firm characteristics, including firm size, revenue, regional composition, and workforce demographics, confirming that the randomization was successful.
Source: German Business Panel Tax Advisor Survey 2025

Figure A.4: Current Generative AI Use by Firm Size



Note: This figure shows the frequency of generative AI use across firms of different sizes: 0-3, 4-7, 8-10, and 11-144 employees. Categories include "Never," "Rarely," "Sometimes," "Often," and "Always."
Source: German Business Panel Tax Advisor Survey 2025

Figure A.5: Belief Updating by Occupation



Note: This figure illustrates belief updating about automation rates for all four elicited occupations based on regression equation (1), where belief shifts in automation potential are modeled as a function of prior expectations and information treatment exposure. The individual γ_o parameters represent the slops of the red lines. The horizontal axis represents respondents' prior beliefs, and the vertical axis shows their posterior beliefs about automation rates. Light blue dots represent individual values in the control group, while red triangles denote those who receive any treatment. Larger, darker markers indicate averages for 10 quantile bins within each group. The dashed 45 degree line represents no belief updating.

Source: German Business Panel Tax Advisor Survey 2025

Table A.2: First-Stage Regressions

	(1) Tax Clerk	(2) Cert. Tax Assistant	(3) Tax Advisor	(4) Auditor
High × Prior TA	0.194**	0.053	-0.029	-0.114
	(0.080)	(0.076)	(0.070)	(0.078)
Low × Prior TA	0.422***	0.313***	-0.126*	0.050
	(0.079)	(0.074)	(0.069)	(0.076)
All × Prior TA	0.201**	0.038	0.141*	-0.117
	(0.086)	(0.081)	(0.075)	(0.083)
High × Prior Auditor	-0.130*	-0.024	-0.008	0.076
	(0.067)	(0.063)	(0.058)	(0.064)
Low × Prior Auditor	-0.232***	-0.157**	-0.036	-0.082
	(0.066)	(0.062)	(0.057)	(0.063)
All × Prior Auditor	-0.101*	-0.050	-0.161***	-0.203***
	(0.061)	(0.057)	(0.052)	(0.058)
High × Prior CTA	0.055	-0.160*	-0.066	-0.099
	(0.093)	(0.090)	(0.080)	(0.091)
Low × Prior CTA	-0.162*	-0.307***	-0.227***	-0.237***
	(0.088)	(0.084)	(0.076)	(0.086)
All × Prior CTA	-0.016	-0.186**	-0.103	-0.009
	(0.089)	(0.084)	(0.077)	(0.085)
High × Prior Clerk	-0.171**	0.098	0.076	0.063
	(0.080)	(0.077)	(0.069)	(0.078)
Low × Prior Clerk	-0.008	0.173**	0.335***	0.202***
	(0.081)	(0.076)	(0.070)	(0.078)
All × Prior Clerk	-0.115	0.114	0.166**	0.222***
	(0.080)	(0.076)	(0.069)	(0.077)
Treatment High Skilled	17.213***	11.036***	5.102**	5.213**
	(2.595)	(2.442)	(2.234)	(2.459)
Treatment Low Skilled	5.206**	4.523*	3.774*	5.104**
	(2.607)	(2.461)	(2.247)	(2.480)
Treatment All	14.653***	12.154***	5.243**	4.951**
	(2.667)	(2.507)	(2.295)	(2.516)
Prior Tax advisor	-0.122**	-0.038	0.701***	0.174***
	(0.058)	(0.054)	(0.052)	(0.057)
Prior Auditor	0.102**	0.069*	0.146***	0.833***
	(0.043)	(0.041)	(0.038)	(0.041)
Prior Cert. tax assist	0.047	0.910***	0.126**	0.077
	(0.057)	(0.054)	(0.050)	(0.055)
Prior Tax clerk	0.847***	-0.049	-0.095**	-0.081
	(0.055)	(0.051)	(0.047)	(0.053)
Constant	8.088***	6.846***	4.141**	3.526**
	(1.886)	(1.772)	(1.620)	(1.775)
F-Statistic	186.78	284	177.32	295.27
N	1202	1195	1200	1183
R^2	0.68	0.69	0.65	0.71

NOTE: This table reports the OLS first stage of our IV design based on regression equation (1) in which the dependent variable is the respondents posterior belief about the automatability of the occupation named in the column. Treatment main effects capture level shifts in posteriors, while the interaction terms identify learning rates; the large firststage Fstatistics reported at the bottom indicate strong instrument relevance. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.3: Second Stage: Employment and Revenue Outcomes

	(1) Expected Firing Share	(2) Expected Hiring Share	(3) Expected Cost Change	(4) Expected Revenue Change	(5) Expected Profit Change	(6) Expected Wage Change
Pred. Posterior Tax advisors	-0.0016	0.0002	0.0001	-0.0006*	0.0001	-0.0004
	(0.00624)	(0.00810)	(0.00013)	(0.00036)	(0.00083)	(0.00043)
Pred. Posterior Auditors	0.0051	0.0067	-0.0001	0.0019**	0.0017***	0.0004***
	(0.00647)	(0.00668)	(0.00056)	(0.00080)	(0.00053)	(0.00014)
Pred. Posterior Certified tax assistants	-0.0038	-0.0043	-0.0005	-0.0010	-0.0003	0.0002
	(0.00417)	(0.00479)	(0.00068)	(0.00100)	(0.00034)	(0.00047)
Pred. Posterior Tax clerks	0.0022	0.0022	-0.0000	0.0012	0.0009	-0.0000
	(0.00333)	(0.00352)	(0.00121)	(0.00101)	(0.00059)	(0.00020)
Constant	0.2446***	0.0535	0.0397	0.0565***	0.0074	0.0517***
	(0.06193)	(0.09798)	(0.03978)	(0.00922)	(0.02221)	(0.00270)
R^2	0.013	0.013	0.002	0.019	0.066	0.004
N	932	940	750	754	747	1097

Note: This table reports second-stage results from an instrumental variables (IV) regression of equation (2) estimating the effect of updated automation beliefs on respondents expectations about employment, wages, and financial firm outcomes. Each column uses the fitted posterior beliefs as the endogenous regressor, instrumented via the randomized information treatment. The dependent variables are drawn from questions on expected hiring and firing from 2025 to 2027, AI-induced cost, revenue, and profit changes, and expected wage changes. Standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.4: Second Stage: Revenue per hour by occupation

	(1) Tax Clerk	(2) Certified Tax Assistant	(3) Tax Advisor	(4) Auditor
Pred. Posterior Tax advisors	-0.0038***	-0.0024*	0.0007	-0.0023
	(0.00114)	(0.00128)	(0.00119)	(0.00188)
Pred. Posterior Auditors	0.0069***	0.0039***	0.0020***	0.0062***
	(0.00243)	(0.00091)	(0.00047)	(0.00211)
Pred. Posterior Certified tax assistants	-0.0007	0.0028***	0.0005	-0.0014
	(0.00196)	(0.00101)	(0.00044)	(0.00193)
Pred. Posterior Tax clerks	0.0039***	0.0007	0.0004	0.0015
	(0.00122)	(0.00074)	(0.00035)	(0.00133)
Constant	-0.0213	0.0010	0.0306*	-0.0120
	(0.03783)	(0.01984)	(0.01760)	(0.01871)
R^2	0.082	0.118	0.107	0.106
N	835	834	839	818

Note: This table reports second-stage results from an instrumental variables (IV) regression estimating the effect of updated automation beliefs on respondents expectations about revenues per hour in specific occupations. Each column uses the fitted posterior beliefs as the endogenous regressor, instrumented via the randomized information treatment. Standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.5: Second Stage: Automation Potential Dummies

	(1) Tax Filing	(2) Payroll Accounting	(3) Tax Consulting	(4) Succession Advisory	(5) International Tax
Pred. Posterior Tax advisors	-0.0002	0.0007	0.0055***	0.0022	0.0013
	(0.00082)	(0.00059)	(0.00097)	(0.00172)	(0.00125)
Pred. Posterior Auditors	0.0015	0.0006	0.0018*	0.0011	0.0024***
	(0.00132)	(0.00068)	(0.00109)	(0.00087)	(0.00065)
Pred. Posterior Certified tax assistants	0.0006	0.0002	-0.0006	-0.0007	-0.0004
	(0.00134)	(0.00034)	(0.00104)	(0.00162)	(0.00080)
Pred. Posterior Tax clerks	0.0025***	0.0022***	-0.0010	0.0004	-0.0006
	(0.00053)	(0.00014)	(0.00141)	(0.00036)	(0.00076)
Constant	0.6006***	0.6402***	0.1138**	-0.0003	0.0365
	(0.03116)	(0.01054)	(0.04975)	(0.01529)	(0.02375)
R^2	0.046	0.027	0.05	0.024	0.021
N	1175	1175	1175	1175	1175

Note: This table reports second-stage results from an instrumental variables (IV) regression estimating the effect of updated automation beliefs on respondents expectations about the automation potential of specific tasks. Each column uses the fitted posterior beliefs as the endogenous regressor, instrumented via the randomized information treatment. Standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.6: Second Stage: New Task Dummies

	(1) Legal Tech	(2) Compliance	(3) Prompt Engineering	(4) Quality Assurance
Pred. Posterior Tax advisors	0.0003	0.0015*	0.0035*	-0.0003
	(0.00049)	(0.00089)	(0.00196)	(0.00075)
Pred. Posterior Auditors	0.0047***	0.0001	0.0022*	0.0002
	(0.00071)	(0.00076)	(0.00122)	(0.00033)
Pred. Posterior Certified tax assistants	-0.0001	-0.0019**	0.0016	0.0009
	(0.00057)	(0.00075)	(0.00202)	(0.00072)
Pred. Posterior Tax clerks	-0.0004	0.0017*	-0.0018	0.0013
	(0.00142)	(0.00091)	(0.00156)	(0.00113)
Constant	0.1518***	0.5109***	0.1894**	0.7551***
	(0.03873)	(0.03191)	(0.08330)	(0.02051)
R^2	0.031	0.004	0.036	0.015
N	1096	1096	1096	1096

Note: This table reports second-stage results from an instrumental variables (IV) regression estimating the effect of updated automation beliefs on respondents expectations about new tasks being required due to automation. Each column uses the fitted posterior beliefs as the endogenous regressor, instrumented via the randomized information treatment. Standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: Second Stage: Training Dummies

	(1) Plans to train employees	(2) Plans general training	(3) Plans specialized training	(4) Plans other training
Pred. Posterior Tax advisors	-0.0010	0.0004	0.0008	-0.0011
	(0.00094)	(0.00054)	(0.00153)	(0.00092)
Pred. Posterior Auditors	0.0003	0.0010	0.0004	0.0015***
	(0.00067)	(0.00126)	(0.00072)	(0.00039)
Pred. Posterior Certified tax assistants	0.0030***	-0.0042**	0.0024***	0.0010**
	(0.00079)	(0.00202)	(0.00073)	(0.00045)
Pred. Posterior Tax clerks	0.0015	0.0036**	-0.0017*	-0.0010***
	(0.00114)	(0.00161)	(0.00093)	(0.00019)
Constant	0.5611***	0.3199***	0.4206***	0.0768***
	(0.02786)	(0.03969)	(0.02948)	(0.01578)
R^2	0.034	0.002		0.009
N	1166	888	888	888

Note: This table reports second-stage results from an instrumental variables (IV) regression estimating the effect of updated automation beliefs on respondents expectations about intentions to train employees. Each column uses the fitted posterior beliefs as the endogenous regressor, instrumented via the randomized information treatment. Standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

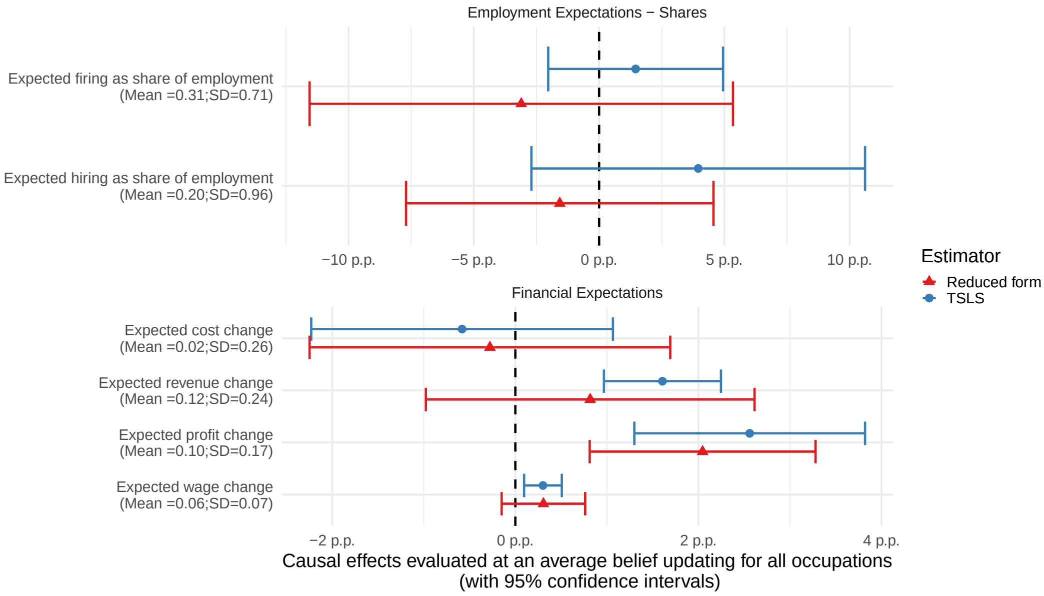
Table A.8: Second Stage: Attitudes and Actions

	(1) Probability of changing occupation	(2) Plans to adopt AI solutions	(3) Information seeking on AI solutions	(4) Sees automation as an Opportunity
Pred. Posterior Tax advisors	0.0026***	0.0047*	0.0005**	0.0012
	(0.00047)	(0.00244)	(0.00024)	(0.00107)
Pred. Posterior Auditors	-0.0001	0.0001	0.0004	0.0001
	(0.00050)	(0.00386)	(0.00077)	(0.00110)
Pred. Posterior Certified tax assistants	-0.0002	-0.0030**	-0.0009	0.0016***
	(0.00017)	(0.00149)	(0.00116)	(0.00045)
Pred. Posterior Tax clerks	-0.0004	0.0066***	0.0020	0.0017**
	(0.00025)	(0.00191)	(0.00129)	(0.00074)
Constant	0.0655***	0.3342***	0.6950***	0.4701***
	(0.01883)	(0.05712)	(0.02851)	(0.03316)
R^2	0.024	0.095	0.021	0.046
N	1174	239	1180	1182

Note: This table reports second-stage results from an instrumental variables (IV) regression estimating the effect of updated automation beliefs on respondents expectations about attitudes to job change and automation. Each column uses the fitted posterior beliefs as the endogenous regressor, instrumented via the randomized information treatment. Standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

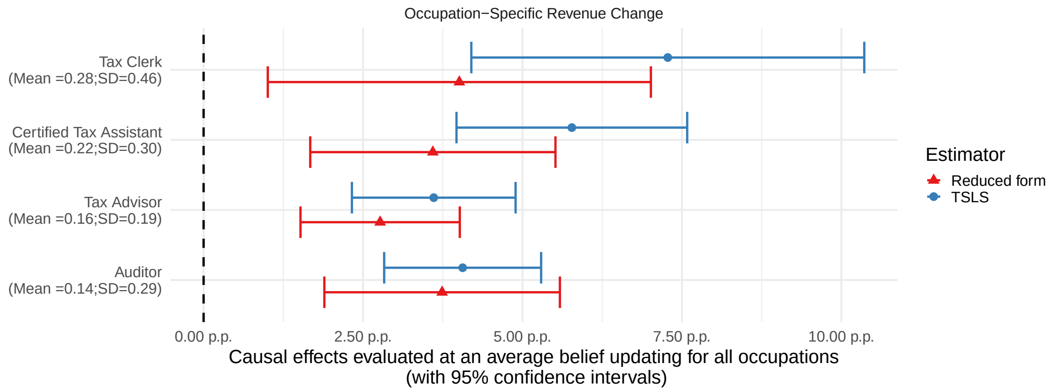
B Reduced Form Estimates

Figure B.6: Comparing reduced form and IV estimates: Main Outcomes



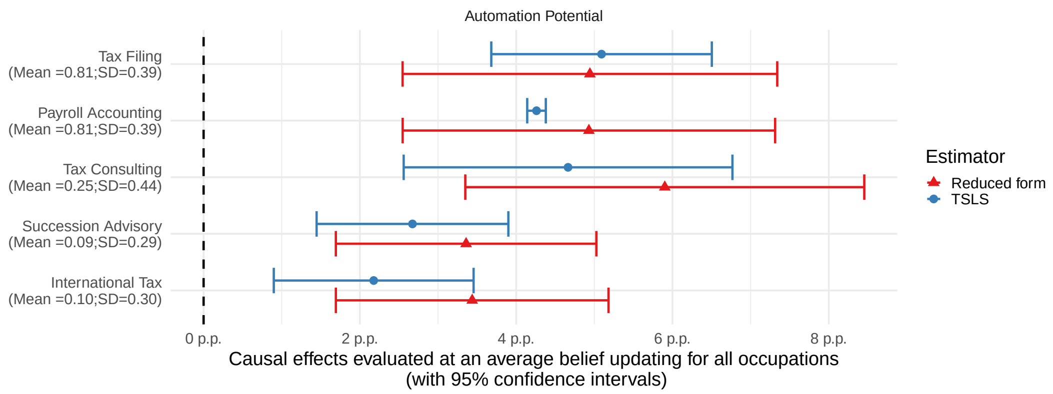
Note: Coefficient plots contrasting reduced-form and 2SLS (IV) effects of information-induced belief updating on employment and financial expectations. The second-stage regression is second-stage regression is given in equation (2). The reduced form regression is $\mathrm{Y}_{io} = \alpha_o + \beta_o \cdot \mathrm{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \mathrm{prior}_{io}) + u_{io}$. Effects are evaluated at the sample-average belief updating across occupations; points are estimates and bars are 95% confidence intervals. Units are percentage points.
Source: German Business Panel Tax Advisor Survey 2025

Figure B.7: Comparing reduced form and IV estimates: Outcomes by Occupation



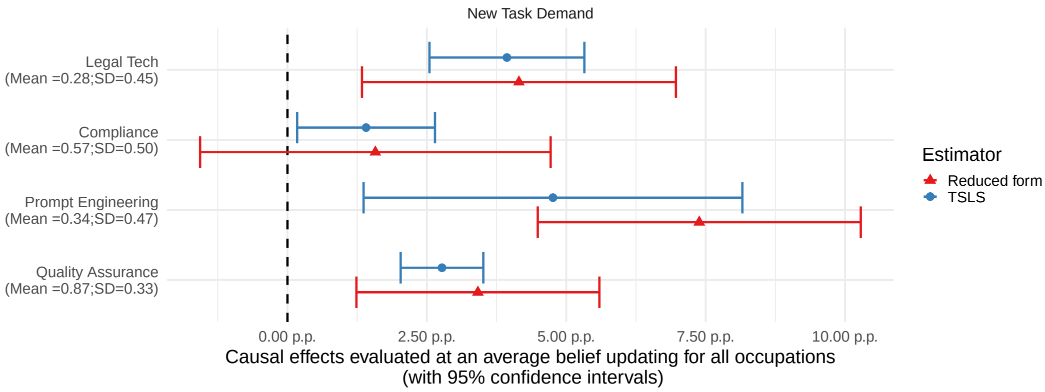
Note: Reduced-form vs. 2SLS (IV) estimates on revenue per hour by occupation group. The second-stage regression is second-stage regression is given in equation (2). The reduced form regression is $\mathrm{Y}_{io} = \alpha_o + \beta_o \cdot \mathrm{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \mathrm{prior}_{io}) + u_{io}$. Effects reflect the impact of belief updating; panels are scaled in percentage points and show point estimates with 95% confidence intervals, evaluated at the average belief updating.
Source: German Business Panel Tax Advisor Survey 2025

Figure B.8: Comparing reduced form and IV estimates: Automation-Potential Dummies



Note: Comparison of reduced-form and 2SLS (IV) effects of belief updating on automation potential dummies. The second-stage regression is second-stage regression is given in equation (2). The reduced form regression is $\mathrm{Y}_{io} = \alpha_o + \beta_o \cdot \mathrm{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \mathrm{prior}_{io}) + u_{io}$. Estimates are reported in percentage points with 95% confidence intervals and are evaluated at the sample-average belief updating across occupations.
Source: German Business Panel Tax Advisor Survey 2025

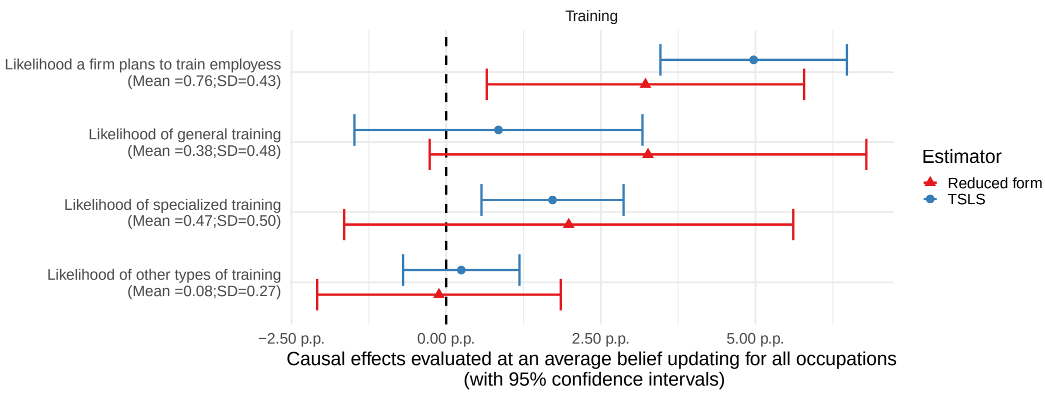
Figure B.9: Comparing reduced form and IV estimates: New Task Dummies



Note: Reduced-form and 2SLS (IV) estimates for outcomes related to the introduction of new tasks due to automation. The second-stage regression is second-stage regression is given in equation (2). The reduced form regression is $\mathrm{Y}_{io} = \alpha_o + \beta_o \cdot \mathrm{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \mathrm{prior}_{io}) + u_{io}$. Effects are evaluated at the average belief updating; units are percentage points and error bars denote 95% confidence intervals.

Source: German Business Panel Tax Advisor Survey 2025

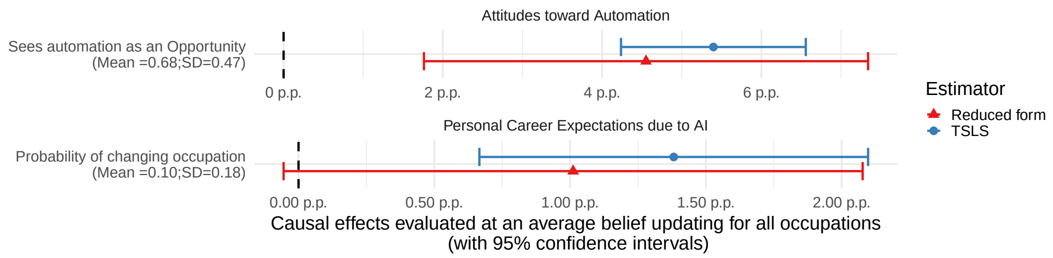
Figure B.10: Comparing reduced form and IV estimates: Training and Skill Investment



Note: Coefficient plots comparing reduced-form and 2SLS (IV) effects of belief updating on training and upskilling outcomes. The second-stage regression is second-stage regression is given in equation (2). The reduced form regression is $\mathrm{Y}_{io} = \alpha_o + \beta_o \cdot \mathrm{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \mathrm{prior}_{io}) + u_{io}$. Estimates are in percentage points, evaluated at the sample-average belief updating, with 95% confidence intervals.

Source: German Business Panel Tax Advisor Survey 2025

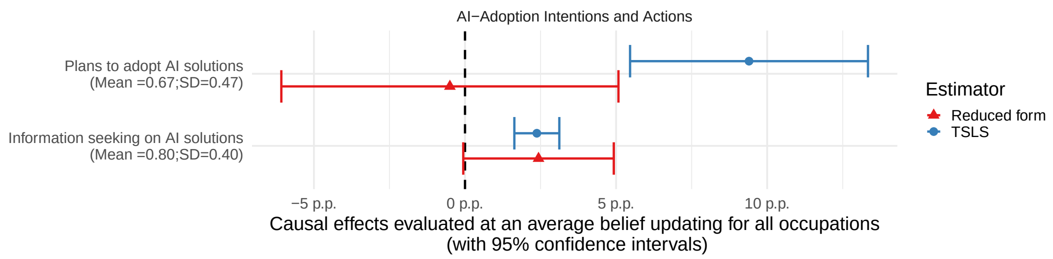
Figure B.11: Comparing reduced form and IV estimates: Attitudes and career plans



Note: Coefficient plots comparing reduced-form and 2SLS (IV) effects of belief updating on attitudes and career plans. The second-stage regression is second-stage regression is given in equation (2). The reduced form regression is $\text{Y}_{io} = \alpha_o + \beta_o \cdot \text{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \text{prior}_{io}) + u_{io}$. Estimates are in percentage points, evaluated at the sample-average belief updating, with 95% confidence intervals.

Source: German Business Panel Tax Advisor Survey 2025

Figure B.12: Comparing reduced form and IV estimates: AI adoption intentions an actions



Note: Coefficient plots comparing reduced-form and 2SLS (IV) effects of belief updating on AI adoption intentions an actions. The second-stage regression is second-stage regression is given in equation (2). The reduced form regression is $\text{Y}_{io} = \alpha_o + \beta_o \cdot \text{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \text{prior}_{io}) + u_{io}$. Estimates are in percentage points, evaluated at the sample-average belief updating, with 95% confidence intervals.

Source: German Business Panel Tax Advisor Survey 2025

C Identification of Effect of Automatability Beliefs on Outcomes

Our information intervention shifts respondents' beliefs about the automation potential of specific occupations. To interpret these belief shifts as causal in a two-stage least squares framework, we rely on a simple Bayesian learning model and derive a Wald estimator that recovers the causal effect of beliefs on outcomes. We show why this is the case, using a single binary treatment and single prior/posterior pair for notational simplicity. However, the logic extends directly to multiple treatment arms and multiple prior/posterior belief pairs. Each treatment arm provides a different signal (e.g., about high-skilled or low-skilled occupations), leading within participants to updates that can be written as a convex combination of the prior belief and the signal. The aim is to identify the causal effect β_1 using an instrumental variables approach, illustrated with the simple Wald estimator.

Bayesian Belief Updating. Let respondents i begin with a prior belief prior_i about the automatability of an occupation. The information treatment provides a signal signal_i, an expert assessment from the Job-Futuromat. If respondents update rationally in a Bayesian manner, the posterior belief posterior_i reflects a convex combination of prior and signal:

$$\text{posterior}_i = (1 - a_i)\,\text{prior}_i + a_i\,\text{signal}_i,$$

where $a = \mathbb{E}[a_i], a_i \in [0,1]$ denotes the learning rate: the weight placed on the new information. This can be rewritten as $\text{update}_i = a_i\,(\text{signal}_i - \text{prior}_i)$.

First Stage. To estimate belief updating empirically, we regress the posterior on the prior, treatment, and their interaction:

$$\text{posterior}_i = \alpha_0 + \alpha_1\,\text{prior}_i + \delta\,D_i + \gamma\,D_i \times \text{prior}_i + \epsilon_i, \tag{4}$$

where D_i is the treatment indicator. If $D_i = 0$ respondents do not receive a signal and thus have no reason to change their beliefs. Their posteriors equal their priors on average, implying $\alpha_0 = 0$ and $\alpha_1 = 1$ for the pure control group. We can solve under these parameters and $D_i = 1$ for:

$$\delta = a \cdot \mathbb{E}[\text{signal}_i], \qquad \gamma = -a.$$

Reduced Form. We use the exogenous variation in posteriors induced by the information treatment to estimate the causal effect of belief changes on outcomes. In the second stage, we model:

$$\text{outcome}_i = \beta_0 + \beta_1 \, \text{posterior}_i + \nu_i, \tag{5}$$

where posterior_i is the posterior belief formed after treatment.

Inserting equation (4) into (5) gives the reduced form

$$\text{outcome}_i = \pi_0 + \pi_1 \, \text{prior}_i + \pi_2 \, D_i + \pi_3 \, (\text{prior}_i \times D_i) + \upsilon_i. \tag{6}$$

Testable restrictions are $\hat{\pi}_3 = \hat{\pi}_2/\mathbb{E}[\text{signal}_i]$ and $\hat{\pi}_1/\hat{\alpha}_1 = \hat{\pi}_2/\hat{\delta} = \hat{\pi}_3/\hat{\gamma}$. With the pure control group parameters $\alpha_0 = 0$ and $\alpha_1 = 1$, equation (6) also identifies β_1, since $\pi_0 = \beta_0 + \beta_1 \, \alpha_0, \pi_1 = \beta_1 \, \alpha_1$.

Wald Estimator. To construct the Wald estimator, we consider differences in expectations across treatment for individuals i in the treatment group and control respondents j. The average priors in both groups are statistically equal, such that $\mathbb{E}[\text{prior}_i \mid D_i = 1] = \mathbb{E}[\text{prior}_j \mid D_j = 0]$, since groups are randomized:

$$\begin{aligned}\Delta D &= \mathbb{E}[\text{posterior}_i \mid D_i = 1] - \mathbb{E}[\text{posterior}_j \mid D_j = 0] \\ &= a\mathbb{E}[\text{signal}_i \mid D_i = 1] - a\mathbb{E}[\text{prior}_i \mid D_i = 1] \\ &= \delta + \gamma \cdot \mathbb{E}[\text{prior}_i] = \mathbb{E}[\text{update}_i],\end{aligned}$$

$$\begin{aligned}\Delta Y &= \mathbb{E}[\text{outcome}_i \mid D_i = 1] - \mathbb{E}[\text{outcome}_j \mid D_j = 0] \\ &= \beta_1(\delta + \gamma \cdot \mathbb{E}[\text{prior}_i]) = \beta_1 \, \mathbb{E}[\text{update}_i].\end{aligned}$$

Taking the ratio gives the Wald grouping estimator:

$$\beta_{WG} = \frac{\Delta Y}{\Delta D} = \beta_1.$$

While posterior beliefs and outcome expectations may both be influenced by baseline characteristics such as ability or experience, we do not need to control for them explicitly. This is because we observe each respondent's prior belief prior_i immediately before treatment. That is, any effect of baseline characteristics on posteriors is mediated through the prior. Conditional on prior_i, the treatment-induced change in posterior beliefs is exogenous, since it only depends on the exogenously given signal.

Interpretation and Identification. This approach identifies the causal effect of belief changes on outcome expectations (β_1), even when posterior beliefs and outcomes are both correlated with unobserved baseline characteristics such as ability. The key is that we observe the prior belief prior_i immediately before treatment, and can condition on it directly in the reduced form. In the Wald estimator, the prior drops out. Since the treatment is randomly assigned and the prior captures pre-treatment heterogeneity, the variation in posteriors induced by the treatment is exogenous. No additional controls are needed in either stage. Identification further requires that the information signal is constant as in our application (or has the a constant expectation across treated respondents). The exclusion restriction requires that the treatment affects outcomes only through its effect on posterior beliefs, which is unlikely to be violated, since information that affects treatment participants differently is not likely to occur within the typically short completion time of the survey.

D Descriptive Statistics

Table D.9: Summary Statistics

	Mean	SD	Min	P25	Median	P75	Max	Histogram
Female (Dummy)	0.34	0.47	0.00	0.00	0.00	1.00	1.00	
Tax Advisor (Dummy)	0.99	0.11	0.00	1.00	1.00	1.00	1.00	
Legal Form GmbH (Dummy)	0.30	0.46	0.00	0.00	0.00	1.00	1.00	
Legal Form Partner Association (Dummy)	0.20	0.40	0.00	0.00	0.00	0.00	1.00	
Age	50.23	10.43	20.00	43.00	52.00	58.00	80.00	
Total Employees	104.54	1,140.94	0.00	4.00	9.00	22.75	40,000.00	
Firing share (next three years)	0.22	0.24	0.00	0.05	0.15	0.31	1.00	
Hiring share (next three years)	0.18	0.85	0.00	0.02	0.09	0.18	21.43	
Revenue (thousand EUR)	1,524.11	1,943.75	0.00	280.91	800.00	1,900.00	10,000.00	
Expected Revenue Change (Pct.)	0.12	0.22	-0.50	0.00	0.10	0.20	5.00	
Expected Profit Change (Pct.)	0.10	0.16	-0.50	0.00	0.10	0.15	2.00	
Expected Cost Change (Pct.)	0.02	0.24	-1.00	-0.10	0.00	0.10	5.00	
Expected Wage Change (Pct.)	0.06	0.07	-0.50	0.03	0.05	0.10	1.20	

Note: This table presents summary statistics for the full survey data including big firms with more than 150 employees or more than 10 Mio. Euro of revenue.
Source: German Business Panel Tax Advisor and Auditor Survey 2025

E Questionnaire

Table E.1: Relevant questions from the GBP Tax Advisor survey

No.	Question	Answer Options	
Q1	What is your current employment status?	- Employed - Self-employed	
Q2	Which of the following positions best describes your role?	- Board Member/Executive Management - Senior Partner - Partner - Director - Senior Manager - Manager - Senior Consultant - Consultant, expert, analyst - student, intern	
Q3	In your role as `selected role`: Do you have personnel responsibility?	- Yes - No	
Q4	In your professional role: How often do you work with AI-powered tools that generate text independently? For example, ChatGPT, Claude, etc.	- Always - Often - Sometimes - Rarely - Never	
Q5	In your company: How many employees are working in the following professions? Please provide the number in full-time equivalents.	- Tax consultant - Chartered accountant - Tax specialist - Tax clerk	[0,100000] [0,100000] [0,100000] [0,100000]
Q6	What do you estimate: How much of the core activities in the following professions can be automated by 2024? Please provide a percentage.	- Tax consultant - Chartered accountant - Tax specialist - Tax clerk	[0,100] [0,100] [0,100] [0,100]
Q7	If you think again: What do you think now? Would you like to adjust your information?	- Tax consultant - Chartered accountant - Tax specialist - Tax clerk	[0,100] [0,100] [0,100] [0,100]

No.	Question	Answer Options
Q8	From your company's perspective: Which of the following areas of responsibility have emerged due to automation in tax consulting?	- Quality control of automation results - Data protection and compliance monitoring - Prompt engineering - Application and support of legal tech/large language models (LLMs) - Other areas of responsibility
Q9	From your company's perspective: How many new employees do you plan to hire in the coming years? How many of them will be for new areas of responsibility created by automation? Note: Please indicate the number of new hires in each year in full-time equivalents.	2025 2026 2027 Total new hires Of which employees for areas of responsibility created by automation
Q10	Regarding your personnel planning: How would you proceed if tasks could be replaced by automation? Please provide the number of affected staff.	2025 2026 2027 Assign employees new tasks Dismiss employees
Q11	How do you perceive the changes in your profession due to automation?	- As a threat - As an opportunity for professional development - Neither a threat nor an opportunity
Q12	Which profession would you most likely switch to?	- Public Accounting - Tax Consulting - Tax Technology Expert - Prompt Engineer - Data Scientist - No change
Q13	Given the level of automation in your occupation, how likely is it that you would change occupation? Note: 0% (no career change) - 100% (career change)	[0,100]

No.	Question	Answer Options
Q14	How many new employees do you plan to hire in the following occupations in total by 2027? Note: Please indicate the number of new employees in each year in full-time equivalents.	- Tax consultant [0,1000] - Chartered accountant [0,1000] - Tax specialist [0,1000] - Tax clerk [0,1000]
Q15	In which area do you see automation potential in your company?	- Business consulting - Financial accounting - International tax law - Payroll accounting - Succession planning - Tax consulting - Tax declaration
Q16	There are now several new AI solutions for tax advisors. Would you like to learn more about examples of such AI solutions?	- Yes - No
Q17	Have you ever heard of or actively used one of these AI solutions for tax advisors? - Taxy.io: A platform that develops AI solutions specifically for tax advisors. This tool analyzes tax questions and provides precise answers based on specialized literature. - DATEV LexInform AI Assistant (LEA): An AI solution that supports tax advisors in researching legal documents by providing relevant information and sources (e.g., UStAE, BMF letters).	- Yes - No
Q18	How frequently do you use these AI solutions?	- Use them regularly - Use them irregularly - Do not use them

No.	Question	Answer Options
Q19	Do you plan to use AI solutions in the future?	- Yes - No
Q20	What increase in turnover per working hour do you expect for the following professions? Note: Please indicate the expected percentage change (positive or negative values).	- Tax Advisor - Auditor - Tax Clerk - Tax Assistant
Q21	Compared to today: How does your company plan to adjust the average hourly wage for all employees in the next 12 months? Note: Please enter the change in per cent. You can enter positive or negative values.	- Change in hourly wage in per cent
Q22	How much time do you plan to spend on your own digital training in an average week in the future? Note: Please enter the value in hours.	
Q23	Is your company planning investments or further training on automation topics for employees?	- Yes - No
Q24	What kind of investments or further training on automation topics is your company planning?	- General further training (e.g. part-time study) - Specialized further training (e.g. certified fibutronics) - Investments in hardware and software (e.g. ChatGPT, computer) - Other
Q25	What do you estimate for your company? By what percentage will the following variables change through the use of AI? Note: Please enter a value in percent. You can enter positive or negative values.	- Profit Change - Revenue change - Cost change

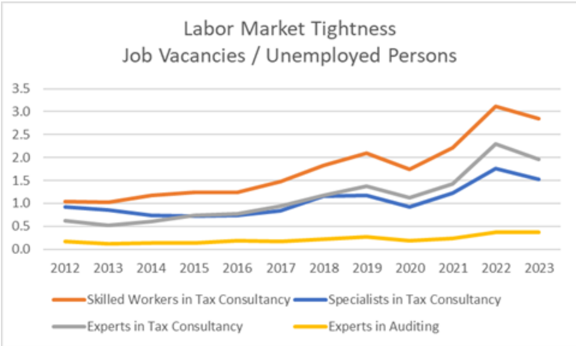
No.	Question	Answer Options
Q26	When were you appointed as a tax consultant or auditor? Note: Please enter the year of your appointment.	- year of appointment - (not yet) appointed
Q27	How would you like to be addressed in a greeting?	- Mr - Ms - Not specified
Q28	When were you born? Note: Please enter your year of birth.	
Q29	What is the legal form of your company?	- Sole proprietorship - GmbH - GmbH and Co. KG - UG - AG - oHG - GbR - PartG - KG - SE - Verein - KGaA - Genossenschaft - Public-law company - Other
Q30	Please enter the annual revenue (in EUR) of your company in the previous calendar year. Note: Please enter a whole number without using thousands or decimal separators.	
Q31	If you could not or did not want to answer our question on revenue, do you think you could at least give us a range in which your revenue lies. Which of the following intervals most closely corresponds to your company's annual revenue in the previous calendar year?	Intervals from less than 50,000 EUR to more than 60,000,000 EUR
Q32	Do you have any comments or questions? Your opinion is important to us!	

Note: The full codebook of the GBP tax advisor survey is available from https://gbpanel.org/.

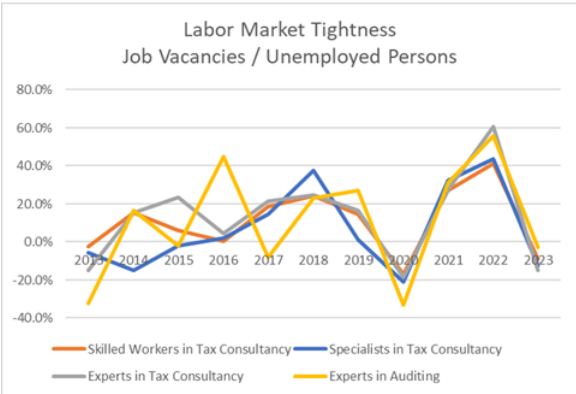
F The German Tax Advisory Industry

Figure F.1: Trends in the Tax Advisory Industry

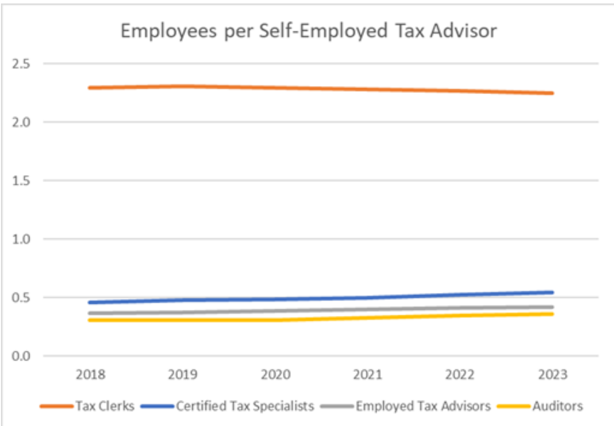
(a) Tightness



(b) Change in Tightness



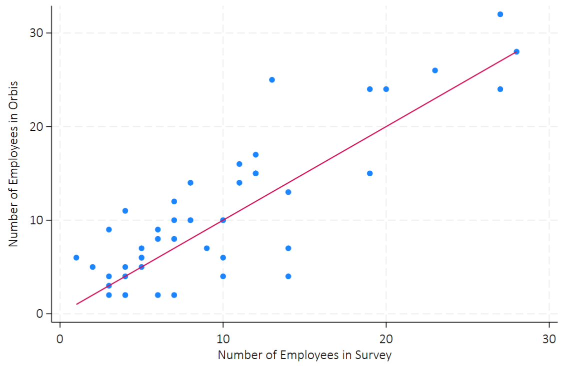
(c) Employees per Self-Employed Tax Advisor



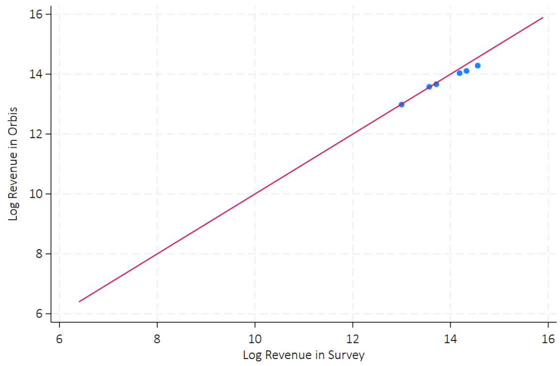
Note: Labor Market Tightness in Tax and Audit Professions (2012-2023). Ratio of vacancies to unemployed persons by occupational category. Orange: Skilled workers in tax consultancy; Blue: Specialists in tax consultancy; Gray: Experts in tax consultancy; Yellow: Experts in auditing. Source: German Federal Employment Agency. Number of Employees per Self-Employed Tax Advisor (2018-2023). The Figure reports the average number of employees in four occupational categories per self-employed tax advisor. Orange: Tax clerks; Blue: Certified tax specialists; Gray: Employed tax advisors; Yellow: Auditors. Source: German Federal Employment Agency, own calculations.

Figure F.2: Comparison of Firm Size Measures from Survey Data and Orbis

(a) Employees in Survey vs. Orbis



(b) Log Revenue in Survey vs. Orbis



Note: Each point is a firm. The left panel compares the number of employees reported in the survey and found in Orbis. The right panel shows the log of revenues. The red line is a linear fit.