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Artificial Intelligence, Tasks, Skills and Wages: Worker-Level Evidence from Germany*

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Abstract

This paper documents novel facts on within-occupation task and skill changes over the past two decades in Germany. In a second step, it reveals a distinct relationship between occupational work content and exposure to artificial intelligence (AI) and automation (robots). Workers in occupations with high AI exposure, perform different activities and face different skill requirements, compared to workers in occupations exposed to robots. In a third step, the study uses individual labour market biographies to investigate the impact on wages between 2010 and 2017. Results indicate a wage growth premium in occupations more exposed to AI, contrasting with a wage growth discount in occupations exposed to robots. Finally, the study further explores the dynamic influence of AI exposure on individual wages over time, uncovering positive associations with wages, with nuanced variations across occupational groups.

Keywords: Artificial intelligence technologies; Task content; Skills; Wages

JEL Codes: J23, J24, J44, N34, O33.

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1. Introduction

Advanced technologies are starting to transform labour markets and the way we perform our jobs. The task model, introduced by Acemoglu and Restrepo (2019), provides a conceptual framework that highlights three main effects of automation technology. The substitution of labour by capital for automated tasks (displacement effect), an increase in the demand for labour for non-automated tasks (productivity effect), and the addition of new tasks (re-instatement effect). Roughly speaking, the relative importance of the three effects then determines how wages respond to automation. While this modelling of automation is highly intuitive, empirical evidence on changes in the task content within narrowly defined occupations is rare.[1]

This paper investigates changes in what individuals do at work, in terms of tasks and skills, and relate these to exposure to new technologies in the form of artificial intelligence (AI) and robots. It then studies how individuals' wage growth is linked to the exposure to these two technologies. Finally, it estimates how time- and occupational-varying changes in exposure to AI progress, both overall and across subdomains of AI, affects individual wages.

For our descriptive analysis, we make use of the German Qualifications and Career Surveys (BIBB-BAuA) conducted over the years 2006, 2012 and 2018. Beside detailed information on employees and their employer, the survey asks individuals about the performance of 18 time-consistent defined tasks and 8 different skill requirements. While the average number of tasks workers perform in their job remains constant over the years, we reveal a considerable change in the importance of tasks and skills within occupations. Specifically, knowledge-intensive or advanced activities (e.g. research, organise, consult) become more important over time, while tasks related to manufacturing (e.g., producing and repairing) and facilitating for others

[1]This is mainly due to data limitations. While the Occupational Information Network (O*NET) allows to identify the task content of occupations, it does not allow to look at time variation within occupations. One exception is the work by Consoli *et al* (2023), who combine the Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network (O*NET), to identify within-occupation task changes in the routine intensity.

(e.g. nursing and cleaning) decline in importance. Importantly, we also document substantial variation across occupations, in the extent how the within-occupation task intensity changes over time. These differences help to explain the differential effects of new technologies on wages across different occupation groups (see below).

In a second step, we combine the BIBB-BAuA data with different measures for AI and robot exposure at the occupation level, to investigate how these new technologies are related to the task and skill content of jobs. Exposure to AI technology has been found to be strongly associated with establishments' hiring patterns (Acemoglu *et al.*, 2022). For AI technology, we use the novel Dynamic Artificial Intelligence Occupational Exposure (DAIOE) index by Engberg *et al* (2023a), and, for robot technology, we make use of the robot index by Webb (2020). Building on Felten *et al.* (2018, 2021), DAIOE uses metrics on the state-of-the-art performance over time of AI across different sub-fields of AI, such as language modelling or image classification, from AI research papers. The data on AI progress are then mapped to those *worker abilities*, such as reasoning, manual dexterity, or vision, to which AI is deemed to be most applicable. To estimate robot exposure, Webb (2020) uses natural language processing (NLP) techniques to link descriptions of patented inventions related to robotics to descriptions of work tasks across occupations.

Combining the BIBB-BAuA data with the two measures, a striking pattern emerges. The relationship between work content and AI exposure is a mirror image of the one between work content and robot exposure. Put differently, workers in occupations with a high AI exposure perform different activities and face different skill requirements, compared to occupations that are exposed to automation (robots). These differences are persistent, even when controlling for differences in the task and skill content of jobs across regions and industries, and when including individual controls, such as education or wages.

These results are motivating our empirical analysis, where we employ the sample of integrated labour market biographies (SIAB) provided by the Institute for Employment Research

(IAB) in Germany, to investigate how technologies are affecting wages. We first examine how changes in individual wages between 2010 and 2017 are correlated with AI and robot exposure. Again, these two technologies differ substantially, now in the way how they are related to wage changes. We document a worker wage growth premium in occupations that are more exposed to AI, but a worker wage growth discount in occupations that are exposed to robots. The results are robust to the inclusion of worker and establishment controls, and additive fixed effects for workers and establishments. In a second step, we then exploit the time-variance of the DAIOE index to uncover the influence from variation of AI exposure over time and across occupations on individual wages. Importantly, variation in AI exposure within and across narrowly defined occupations, allows us to control for worker and occupational fixed effects. Overall, we find positive effects of increase in AI exposure on individual wages between the years 2010 and 2017. Reassuringly, these effects are not driven by any single of the several sub-indices of the DAIOE index. We also reveal heterogeneous effects of changes in the AI exposure across occupational groups. Specifically, we document wage increases for the group of technicians and clerical support and services and sales agent workers when their occupation is more exposed to AI progress, while wages for professionals and operators are affected negatively from an increase in AI exposure.

Thus, our main contribution is to demonstrate how AI is related to changes in the detailed content of and remuneration of work by exploiting granular and representative worker-level data as well as a novel measure of AI occupational exposure (Engberg *et al*, 2023a). Thereby, the paper directly speaks to the expected profound impacts of AI on jobs and wages (Eloundou *et al.*, 2023, OpenAI, 2023, Autor *et al*, 2022). Empirical evidence is however limited in the absence of granular data on firms and individuals (Seamans and Raj, 2018, Frank *et al.*, 2019, Zolas *et al.*, 2021, OECD, 2023). Research on how AI changes the work content and wages has therefore mainly been restricted to aggregate or occupational and state level studies for the USA (Lane and Saint-Martin, 2021).[2] However, Acemoglu *et al.* (2022) use US

[2]Recently, experimental studies on the effects of generative AI in limited tasks related to writing, coding,

job ads data (2010-2018) to document that exposure to AI in 2010 is related to a subsequent churning of skills and a decrease in vacancy postings for non-AI-related jobs, while finding no impact on occupational wages. Alekseeva *et al.* (2021) study AI skill requirements and wages in US job vacancy notes (2010-2019). They find a strong increase in demand for AI skills and an AI wage premium, in particular for managers and in combination with, e.g., software, cognitive and soft skills. In another study, Babina *et al* (2022) find that having employees with AI skills is associated with an up-skilling of the workforce, using job ads and resume data (2016-2018). Finally, Fossen *et al* (2022) use the patent-based measure of occupational exposure to AI, software and robots of Webb (2020) to study individual-level wage changes in the USA (2016-2021). Their results indicate a positive relation between AI exposure and wage growth and the opposite for software and robots.

The paper also contributes to the broader literature on AI and the labour market. Conceptually, according to the framework of Acemoglu and Restrepo (2019), AI may automate work tasks, raise productivity, or create new tasks. AI may also augment or assist workers in existing tasks, increasing labour demand and wages (Bessen *et al*, 2022). Examining how worker tasks and skills change in relation to AI exposure, we find evidence in line with AI automating some shares of work, e.g., for professionals (for whom several tasks become less frequently carried out), and augmenting workers in other tasks, e.g. for non-professionals (for whom more knowledge-intensive tasks become more likely). However, the number of tasks that workers perform does not decrease. These findings are in line with anecdotal evidence from limited surveys, where workers are more inclined to see advantages with AI in terms of efficiency and new or more interesting tasks, rather than the threat of AI automating their work tasks (SACO, 2023). They are also in line with most experimental studies of the recent generative AI technology, where AI appears to complement workers in tasks. Thus, AI seems to further promote the already existing up-skilling documented by, e.g., Atalay *et al.*

consulting, customer services and medical diagnostics have emerged (Brynjolfsson *et al*, 2023, Dell'Acqua *et al*, 2023, Fraser *et al.*, 2023, Gaube *et al.*, 2023, Harskamp and De Clercq, 2023, Noy and Zhang, 2023, Peng *et al.*, 2023).

(2020) for the USA in the 1950-2000 period. Finally, we exploit representative individual-level panel data for Germany to meticulously estimate wage effects from exogenous changes in AI exposure, finding a robust association between changes in exposure to AI and wages. Carrying out these further analysis, we find that the patterns of how changes in the work content relates to AI exposure matters for within-worker wage changes, with the up-skilling for non-professional workers associated with AI exposure also being linked to an increase in wage.

Finally, we contribute by providing micro-level evidence from the largest country of the European Union (EU), namely Germany, which accounts for a quarter of the EU GDP. Germany is the manufacturing hub of the EU, with a relatively large share of mid-sized firms and low unemployment. Fortunate for our empirical analysis, Germany also was early to promote and adopt advanced technologies like artificial intelligence, this since its launch of the "Industrie 4.0"-program in 2013. Like US firms, German firms, and especially the larger ones, could therefore be expected to be early adopters of advanced technologies like AI.[3] With larger firms adopting AI or using more advanced equipment and services that incorporated AI algorithms, a large share of workers in Germany were therefore likely to be exposed to AI progress and this even if the firm did not invest heavily in AI implementation. Early adoption in Germany is also consistent with a relatively large share of German enterprises having adopted AI in 2021, compared to the EU average (Eurostat, 2023).

2. Data and Stylized Facts

We make use of three data sources that provide information on the task content and skill requirements of occupations, the exposure of occupations to advanced technologies, and detailed worker level information. A common variable in all these data sources are detailed

[3] Acemoglu *et al.* (2022) document a strong increase in job ads requiring AI skills from 2010 and onwards, and especially from the mid-2010s. According to a report conducted by Rammer (2022), the share of AI-adopting firms in Germany was between 6-10% around 2020. Moreover, Giering *et al.* (2021) use individual-level German survey data from 2019 and find that up to 45% of workers already engage with AI technologies.

occupation codes, specifically the ISCO-08 occupation classification at different levels of aggregation.[4] To also study potentially heterogeneous associations between technology and the content of work for broader occupational groups, we classify workers as knowledge-intensive business services (KIBS) workers, blue collar workers, and other non-professionals.[5] As shown in Miles *et al.* (1995), KIBS work is intense in cognitive skills and human capital more broadly. Thus, KIBS workers, such as accountants, architects and software developers could therefore be particularly exposed to AI, as indicated in recent experimental studies (Brynjolfsson *et al*, 2023, Dell'Acqua *et al*, 2023, Noy and Zhang, 2023).[6]

2.1. Within-occupation Task and Skill changes

To provide a meaningful analysis of the task content and the skill requirements within occupations, we make use of the German Qualifications and Career Surveys conducted over the years 2006, 2012 and 2018, carried out by the German Federal Institute for Vocational Education and Training (BIBB) and the German Federal Institute for Occupational Safety and Health (BAuA). Each telephone survey is based on around 20,000 employed people aged 15 and over with regular working hours of at least 10 hours per week. The BIBB-BAuA data report detailed information on worker and employer characteristics.[7] Most importantly,

[4]Throughout the paper we use the following levels of aggregation. 1. major group (1-digit) such as '8 - plant and machine operator, and assemblers'; 2. sub-major group (2-digit) such as '81 - stationary plant and machine operators'; 3. minor groups (3-digit) such as '815 - textile, fur and leather products machine operators'; and 4. unit groups (4-digit) such as '8152 - weaving and knitting machine operators'.

[5]Our classification of KIBS workers follows Engberg *et al* (2023b). Specifically, the list of 3-digit ISCO-08 occupation codes for KIBS is 122, 211, 212, 213, 214, 215, 216, 241, 243, 261, 263, 264, 265, 311, 333, 343, 351, 352. The list of 3-digit ISCO-08 occupation codes for blue-collar workers is 711, 712, 713, 721, 722, 723, 731, 732, 741, 742, 751, 752, 753, 754, 811, 812, 813, 814, 815, 816, 817, 818, 821. And, the list of 3-digit ISCO-08 occupation codes for non-professionals is 322, 413, 421, 422, 431, 432, 441, 511, 512, 513, 514, 515, 516, 531, 532, 541, 611, 612, 621, 831, 832, 833, 834, 911, 912, 921, 931, 932, 961, 962. Note, that this classification excludes some occupation codes among the group of managers or professionals.

[6]Studying KIBS is also motivated by the fact that employment in KIBS is larger than employment in manufacturing in several countries and by KIBS distinguishing themselves in terms of high start-up rates compared to manufacturing, being the basis for tomorrow's larger companies (Audretsch *et al.*, 2020).

[7]Specifically, for worker characteristics we use information on hourly gross wage (computed from information on the monthly gross wage and weekly working hours), 3-digit ISCO-08 occupation classification, education (measured in years of schooling), gender, marriage, age, work experience (measured in years in employment using the workers age information and the years of education incl. training), the type of employment (worker, salaried employee, or civil servant), and part-time. Employer characteristics include the industry classification (61 different 2-digit NACE 1.1 industries), regional information (18 different NUTS 2

we observe workers' responses to survey questions that regard the tasks they perform (or not) and the skills that are required in their occupation. The data allows us to distinguish between 18 different tasks, such as: Program a Computer; Developing, researching, constructing; and Transport, Store, Dispatch. The data also includes information on 8 different skill requirements, such as: Knowledge of project management; Knowledge in mathematics, calculus, statistics; and Commercial or business knowledge.

Table A1 in the Online Appendix provides information on the share of workers that perform a specific task and report specific skill requirements in their job, while Table A2 provides summary statistics.[8] Previously, Becker and Muendler (2015) have used the BIBB-BAuA data for the survey years 1979, 1986, 1992, 1999 and 2006.[9] They document a sixfold increase in the average number of tasks performed over the sample period, when using a similar task classification that accounts for 15 different activities. From 2006 onwards, however, the average number of tasks performed by workers remains rather constant. Specifically, using our task classification, the average task number is 8.70, 8.75, and 8.75 for the years 2006, 2012, and 2018.[10]

We start from here and focus on changes in the task composition and the skill requirements within detailed job groups across the years 2006 to 2018. Put differently, we aim to investigate how certain tasks and skill requirements become more or less important. To do so, we compute the relative change in the share of workers that report to perform a specific task and report a specific skill requirement between the survey years 2018 and 2006 within different occupation groups. Figure 1 illustrate these changes for the 18 different activities and 8 skill requirements within the group of KIBS, blue-collar, and non-professional workers. In

regions), and size groups (1 person, 2 p., 3 - 4 p., 5 - 9 p., 10 - 19 p., 20 - 49 p., 50 - 99 p., 100 - 249 p., 250 - 499 p., 500 - 999 p., 1000 and more p.)

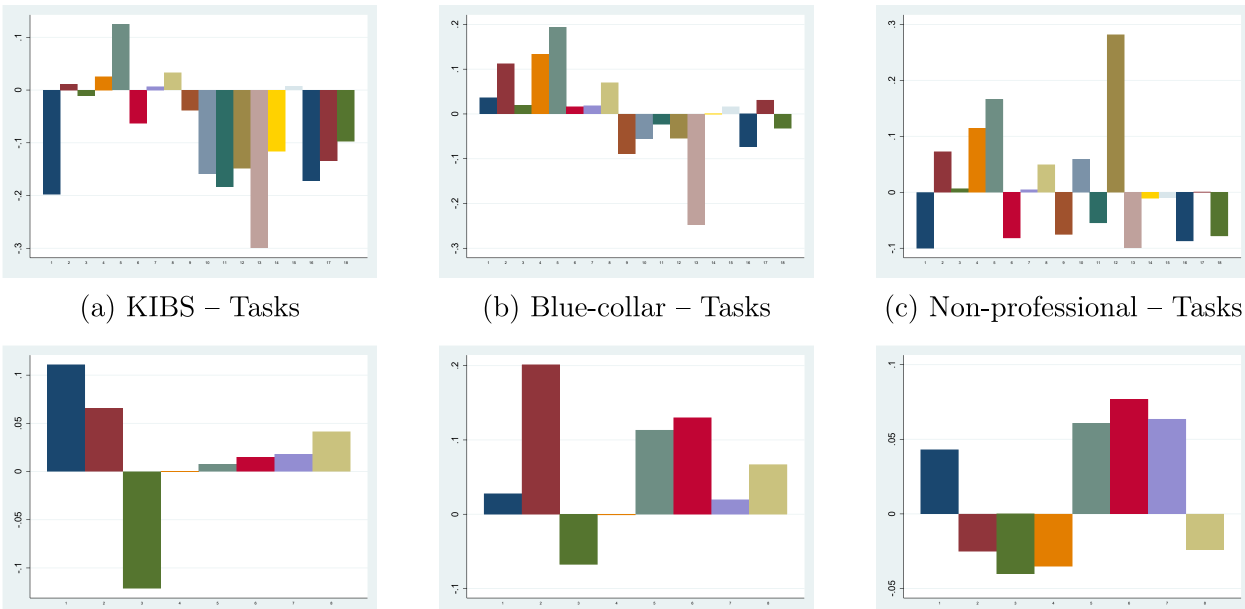
[8] For our analysis on the BIBB-BAuA data, we drop observations with missing information on worker and employee characteristics.

[9] Other important contributions making use of the previous waves and survey questions, include, among other, Acemoglu and Pischke (1998), Spitz-Oener (2006), and Gathmann and Schönberg (2010).

[10] Using the same classification of 15 tasks as in Becker and Muendler (2015), the average task number is around 7.

Figures A1, A2, A3, and A4 in the Online Appendix, we repeat the exercise for 9 different ISCO-08 major groups (Managers; Professionals; Technicians; Clerical Support; Service & Sales; Agricultural; Craft & Trade; Operators; Elemantary Jobs) and 35 different sub-major groups, denoted by 2-digit ISCO-08 codes.[11]

Figure 1: *Changes in the task composition and skill requirements*



(a) KIBS – Tasks

(b) Blue-collar – Tasks

(c) Non-professional – Tasks

(d) KIBS – Skills

(e) Blue-collar – Skills

(f) Non-professional - Skills

Notes: Panel a-c (d-f) illustrates the change in the share of workers that report performing a specific task (report a specific skill requirement) between 2018 and 2006 within the group of KIBS (knowledge intensive business services), Blue-collar, and non-professional occupations. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 14,722 individuals from BIBB-BAuA survey waves 2006 and 2018.

These figures document a considerable change in the importance of tasks and skills within occupations. For example, according to Panel b) in Figure 1, the share of blue collar workers that report to organise, plan, or prepare (others' work), increases by close to 20% between

[11]Figures A5, A6, A7, A8, and A9, repeat the same exercise by making use of inverse sampling weights.

2006 and 2018, while the importance of task 13 (Nurse, Look After, Cure) declines by around 25%. Furthermore, these figures also document substantial variation across occupations groups. For example, Figure A1 reveals that task 18 (i.e., oversee, control machinery & techn. processes) became more important for the group of agricultural occupations, while it become less important for the group of Service & Sales workers or Operators. Overall, in Figure 1, we note a pattern of "re-skilling" for KIBS and non-professional workers and an "up-skilling" for blue collar workers, both in terms of tasks and skills. These changes occurred in tandem with rapid progress in the capabilities of AI. This was a period of rapid innovation in AI technology; notably, 2012 is regarded as a breakthrough year for AI based on *neural networks*, which enabled subsequent leaps in performance across various AI applications, such as image recognition, speech recognition, or translation. This result is also evident at the 1- and 2-digit occupational levels, for professionals and managers, e.g. production and specialised services managers, but also craft and trade, as well as operators workers, as displayed in Figures A1, A2, A3, and A4.

Generally, tasks that are more knowledge-intensive or advanced, including information gathering, organising, and instructing, become more important over time, while tasks such as repairing, nursing, and producing goods decline in importance.

These figures also document substantial variation across occupations, in the extent how the within-occupation task and skill intensity changes over time. For example, comparing Panel a) and c) in Figure 1, it is evident that many tasks become less frequent for the group of KIBS workers, while for non-professional workers, the task displacement is offset as many other tasks become more important. To our knowledge, such changes in the task-composition and skill requirements within and across narrowly defined occupations, has not been documented so far in the literature.

Interestingly, these changes suggest an adjustment in tasks and skills for KIBS workers to focus more on leadership activities and for non-professionals to partly focus on leadership and partly on, e.g., protecting and accommodating. KIBS workers report to carry out many tasks less frequently than before, except for, e.g., organising and instructing others as well as gathering information. A larger share of KIBS workers also report that they need knowledge of project management, legal knowledge and commercial and business knowledge. For non-professionals, there is also an adjustment in tasks and in terms of skills they increasingly require knowledge related to writing, software applications as well as technical and legal knowledge. Finally, for blue collar workers, we note a pattern of "up-tasking/up-skilling". White-collar tasks become more frequent at work, while other tasks decline in frequency. Even, e.g., procurement becomes more frequent, while substantially decreasing in frequency for KIBS and non-professional workers. Consequently, workers report increasingly needing knowledge in many areas.

2.2. Skills, Tasks and Exposure to AI and Robots

The changes documented in the previous subsection are possibly due to advances in new technologies. Therefore, we now investigate how new technologies are related to the task content and skill requirements of jobs.

Exposure to AI and robots

In the investigation, we use measures for the AI and robot exposure of occupations. Data on robot exposure at the 4-digit occupational level is obtained from Webb (2020), based on the similarity of robot patent texts and occupational task profiles in O*NET.

AI exposure is obtained from the Dynamic Artificial Intelligence Occupational Exposure (DAIOE) index, from Engberg *et al* (2023a). Building on Felten *et al.* (2018, 2021), DAIOE estimates AI exposure by mapping data on technological progress in AI to *worker abilities* in O*NET.

In the DAIOE, progress in AI technology is measured across nine AI *applications*, which in turn can be sorted into three broad areas: language, vision, and games. AI performance is measured through over a hundred *metrics*, or benchmarks, that have been used in AI research. For example, in the *image recognition* application, one metric is the percentage of correctly labelled images in the ImageNet dataset. Another example is ELO score in the game of chess, which is a metric in the *abstract strategy games* application. Observations of the performance of AI systems on metrics are obtained from two repositories with data on AI research, the Electronic Frontier Foundation (EFF) and Papers With Code (PWC). The metrics are re-scaled such that a linear increase in the metric corresponds to an exponential improvement in performance. For each metric a frontier is then derived, which reflects the state-of-the-art (SOTA) performance at a given time. The SOTA frontiers capture many of the well-known breakthroughs in AI research during the years 2010-2023, such as: AlexNet employing a neural network to win the ImageNet image recognition competition in 2012; AlphaGo defeating the human world champion in the game of Go in 2016; Google researchers introducing the *transformer* architecture to improve performance in machine translation of human languages, in 2017; or the publication of GPT-3 by OpenAI in 2020, which achieved high performance across a variety of language tasks, thus showing signs of *generality*. Finally, by taking the average of the slopes of the SOTA frontiers, an estimate of the pace of progress within the application and year is obtained.

Data on the importance of 52 *worker abilities* across occupations are obtained from O*NET. O*NET contains four types of abilities: cognitive, such as *inductive reasoning*; physical, such as *trunk strength*; psychomotor, such as *manual dexterity*; and sensory, such as *depth perception*.

AI applications are then linked to worker abilities through the *mapping matrix* from Felten *et al.* (2018), in which computer scientists have assigned a score to each ability-application cell, reflecting how applicable the AI application is to the worker ability. For example, *image recognition* is scored as highly related to *near vision*; and *language modelling* is scored as being related to *oral comprehension*.

To calculate the change in an occupation's AI exposure during a year, each cell in the mapping matrix is multiplied by its AI progress score. Then, the resulting numbers are summed across abilities, resulting in a score for how the ability's AI exposure changed. Those scores are interacted with the occupation-ability importance scores, and then summed within each occupation to yield its AI exposure score.

The index also assumes that social aspects of work are harder to replace with AI. Thus, the index is discounted based on the sum of the occupation's O*NET scores across six *social skills*, with more points deducted for the most social occupations, such as clergy, nurses, or managers.

Finally, the yearly changes in exposure are summed over time, to produce a *dynamic* index where occupations accumulate exposure points, at different rates, as AI technology progresses across different applications. By feeding just one AI-application at a time into the mapping matrix, it also becomes possible to estimate exposure separately for each of the nine applications. The resulting sub-indices of DAIOE thus shine a light on how occupational exposure differs across different types of AI, and how the timing of AI progress, and the resulting exposure, may have differed across those applications.

According to Engberg *et al* (2023a), high exposure in the DAIOE model suggests that AI is likely to be applicable to the occupation, but whether the exposure will ultimately lead to substitution or augmentation of human labour is beyond the scope of the model.

New technologies, tasks and skills: We combine information on AI and robot exposure with our BIBB-BAuA data from 2006, to investigate how new technologies (robots & AI) are related to the likelihood that workers perform specific tasks.[12] Specifically, we run 18 + 8 probit regressions, where we are regressing the probability of performing a specific task or skill requirement in 2006 on AI and robot exposure, including a set of worker, occupation and plant attributes. Variation comes from differences in AI and robot exposure across 3-digit

[12] As the BIBB-BAuA data only provides 3-digit occupation codes, we compute simple averages of the different technology measures across 4-digit occupations, to obtain exposure measures for 3-digit occupations.

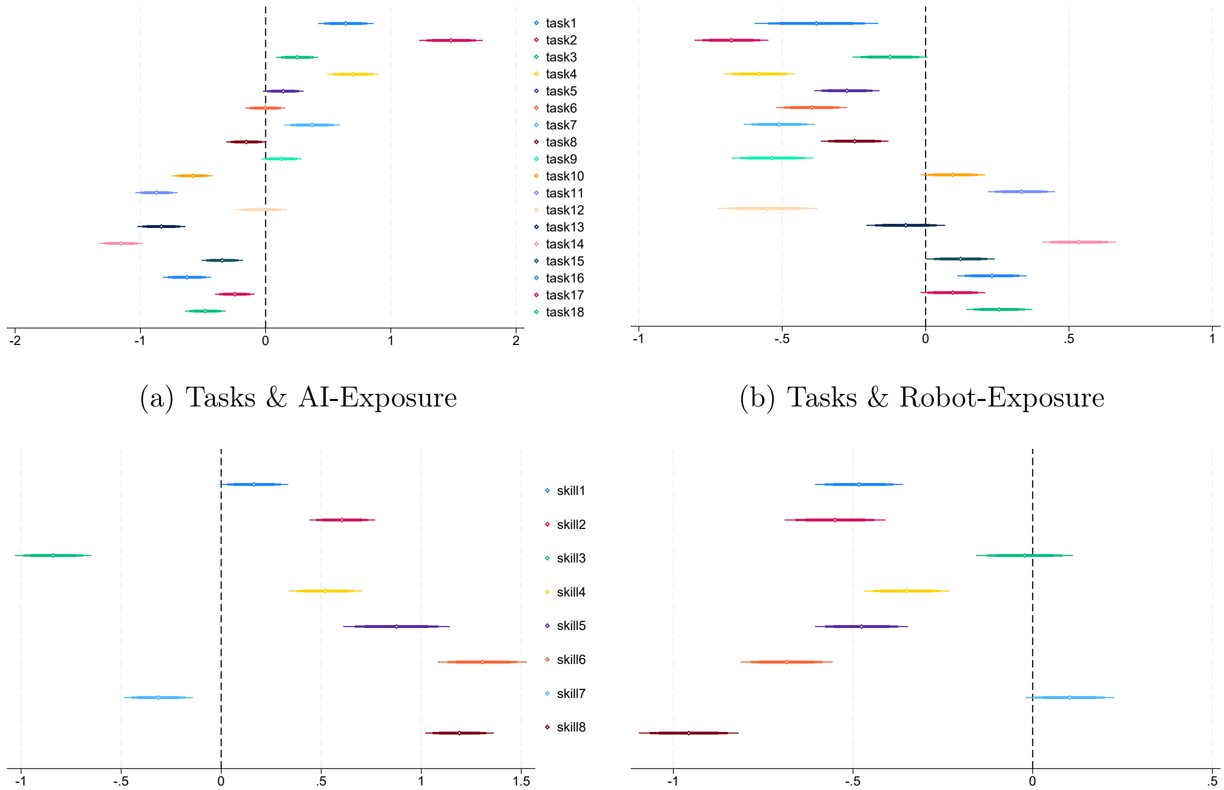
occupations measured in 2017/2018. Thus, the coefficient reflects the correlation between AI or robot exposure and the likelihood of performing a specific task in 2006.

We present estimates of these 26 regressions graphically. Figure 2 reports coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) from estimating probit regressions, including industry, region, plant-size and worker controls.[13] In Figure 2, we note that probabilities of performing tasks and of one's work requiring skills are related to the exposure to AI and robots. However, the relationship between work content and AI exposure is a mirror image of the one between work content and robot exposure. Whereas more knowledge-intensive tasks – tasks 1 to 9 - are more likely to be performed if the occupation is more exposed to AI, they are less likely to be carried out with more occupational exposure to robots. Turning to skills, the ones that are more likely to be carried out with higher AI exposure include leadership, digital, advanced cognitive and language skills as well as skills in the commercial or business domain. These skills are arguably typically associated with positions in the upper hierarchy of organisations, including management but also specialists and analysts. Once more, these patterns are the opposite for robot exposure. The more exposed the occupation is to robots, the less likely it is that skills in the area of, e.g., leadership and language are required. We interpret the "up-tasking/-skilling" pattern related to AI as potentially explained by AI augmenting workers in more exposed occupation or alternatively by AI automating fractions of some tasks, resulting in an increased emphasis on knowledge intensive tasks and skills.

Taking stock, by combining our task and skill data with occupational exposure to advanced technologies, our results reveal that workers in occupations with a high AI exposure are performing different tasks and have different skill requirements, compared to occupations

[13] In the Online Appendix, we provide different versions. Figure A10 and A11 is showing estimates from regressions without all controls, or without worker controls, respectively. Figures A12, A13, and A14 is repeating the exercise for the group of KIBS, Blue-Collar, or Non-professional occupations. Figure A17 is using the AI exposure from Felten *et al.* (2018). We also add the software exposure measure from Webb (2020) to check that the AI exposure measure does not merely capture digitisation generally, see Figure A15. Finally, we also include 1-digit occupational fixed effects, see Figure A16.

Figure 2: *Task, Skills, and Exposure to Technology*



(a) Tasks & AI-Exposure

(b) Tasks & Robot-Exposure

(c) Skills & AI-Exposure

(d) Skills & Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) from estimating probit regressions on the probability of 18 task performance and 8 skill requirement indicators, controlling for industry, region, plant-size and worker controls (incl. log hourly wage, education, age (-squared), experience (-squared, -cubic, - quartic), married, part-time, gender, and type of employment). Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 11,125 individuals from the BIBB-BAuA survey wave 2006. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

with a high robot exposure. This raises the question, if one can we expect similar associations between AI and robot automation and wages. Therefore, we will now introduce a third data source, the Sample of Integrated Labour Market Biographies (SIAB).

2.3. Individual Labour Market Data

The sample of integrated labour market biographies (SIAB) is provided by the Institute for Employment Research (IAB). The SIAB is based on a 2% random sample of all individuals who have ever been registered in the German social security system. In combination with our time-varying AI exposure index, it will allow us to investigate the impact of increasing AI exposure on individual wages, thereby controlling for a rich set of controls, such as worker-, plant-, and occupation fixed effects, and additive fixed effects for workers and plants following the estimation strategy introduced in Abowd *et al.* (1999). We follow Dauth and Eppelsheimer (2020) when preparing the SIAB.[14] We restrict the sample to full-time workers liable to social security between the age 20 and 60 and focus on those years with variation in our AI exposure index, i.e., 2010 to 2017. Summary statistics are provide in Table A3 in the Online Appendix.

3. Empirics

So far, our findings highlight notable distinctions in the tasks performed and skill requirements of workers in occupations characterised by high AI exposure compared to those with a high robot exposure. A pivotal question arises: will the impacts on wages be similar for AI and robot automation? To address this question, we undertake a twofold analysis. First, we examine how changes in individual wages between 2010 and 2017 correlate with AI and robot exposure. Second, we leverage the time-variant DAIOE index to uncover the influence variation of AI exposure over time and across occupations on individual wages. Throughout the following analysis, we will exploit variations in exposure to technology across 365 different 4-digit occupation codes.

[14] In the SIAB, wages above the upper earnings limit for statutory pension insurance are right-censored. As standard, we replace censored wages with imputed wages, by following the methodology in Card *et al* (2013).

3.1. Wage Growth: AI vs Robots

To study the relationship between wage changes and exposure to AI and robot exposure, we estimate variations of the following regression

$$\Delta \ln(\text{wage})_{ioj} = \beta' \text{Exp}_{\mathbf{o}} + \theta_o + \gamma' \mathbf{x_i} + \lambda' \mathbf{z_j} + \alpha_{(i,\tau)} + \mu_{J(i,t)} + \epsilon_{ioj} \tag{1}$$

where $\Delta \ln(\text{wage})_{i,o,j}$ represents the difference in the log daily wage between 2017 and 2010 for individual i in occupation o at plant j. The vector $\text{Exp}_{\mathbf{o}}$ contains the two main independent variables of interest, i.e. AI exposure and robot exposure. Since the occupational robot index by Webb (2020) does not vary over time, for comparison, we use the occupational AI exposure index (DAIOE) by Engberg *et al* (2023a) for 2017, which is the last year of our sample. On the right-hand side, we include a vector of worker controls $\mathbf{x_i}$, such as gender, experience (-squared, -cubic, -quartic), age (-squared), education, migrant status, indicator variables for whether the worker remained in the same plant and same 4-digit occupation, and an indicator variable for right-censored wage. The vector $\mathbf{z_j}$ captures establishment level controls, including (log) number of workers, industry (3-digit NACE Rev.2) and the region (NUTS 3) the plant is located in. The establishment fixed effect, denoted as $\mu_{J(i,t)}$, serves to control for unobservable time-invariant characteristics inherent to each firm. It is interpreted as a proportional pay premium or discount that establishment j applies uniformly to all its employees. The function $J(i,t)$ associated with the establishment component uniquely identifies the establishment where worker i is employed in year t. Since it is not possible to run individual fixed effects, we employ AKM person-effects, denoted as $\alpha_{(i,\tau)}$, as provided by the IAB (refer to Bellmann *et al* (2020)). These person-effects capture the influence of time-invariant worker characteristics throughout the sample period. The derivation of these AKM effects involves a wage regression, incorporating additive fixed effects for both workers and establishments, aligning with the methodology introduced by Abowd *et al.* (1999).[15] We

[15] AKM effects, provided by the IAB, are based on Bellmann *et al* (2020). The estimation follows Card *et al* (2013), who study the role of establishment specific wage premia in generating recent increases in West

use the AKM effects for the period $\tau = 2010 - 2017$, spanning the length of our sample.

In Table 1, we find a worker wage growth premium for being in an occupation that is more exposed to AI, but a worker wage growth discount of the occupation for being more exposed to robots.

Table 1: AI Exposure, Robot Exposure, and Wage Growth

	Change in log daily wage between 2010 and 2017					
AI-Exposure$_{2017}$	0.0349	0.0497	0.0302	0.0349	0.049	0.0302
	(0.00423)	(0.00776)	(0.0157)	(0.00927)	(0.0147)	(0.0136)
Robot-Exposure$_{2017}$	-0.0157	-0.0199	-0.0305	-0.0157	-0.0199	-0.0305
	(0.00310)	(0.00628)	(0.0166)	(0.00557)	(0.00944)	(0.0146)
Observations	136,296	76,324	76,322	136,296	76,324	76,322
R-squared	0.123	0.314	0.318	0.123	0.314	0.318
Worker Controls	yes	yes	yes	yes	yes	yes
Plant Controls	yes	yes	yes	yes	yes	yes
Worker AKM effect	yes	yes	yes	yes	yes	yes
Plant fixed effects	no	yes	yes	no	yes	yes
3-digit occupation fixed effects	no	no	yes	no	no	yes
Clustered-SE at 4-digit occupation	no	no	no	yes	yes	yes

Notes: The dependent variable in all columns is the difference in the log daily wage between 2017 and 2010. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020). Worker controls include controls for gender, experience (-squared, -cubic, - quartic), age (-squared), education, migrant, indicator variables for same plant and same 4-digit occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security.

In the main text, we focus on the change in the log daily wage between 2010 and 2017 as the main dependent variable. In the Appendix, we repeat the regressions presented in Table 1, with the average yearly wage growth as the dependent variable (see Table A4).[16] Finally, we also replace our AI index, with the AI occupational exposure index from Felten *et al.* (2018).

German wage inequality. For different subintervals, they estimate models with additive fixed effects for workers and establishments following Abowd *et al.* (1999).

[16]We also restrict these regressions to samples of workers who stay in the same occupation (see Table A5), or stay in the same occupation and plant (see Table A6).

3.2. Increased AI exposure and wages

In the final stage of our analysis, we turn our attention to the dynamic nature of our AI exposure measure over time. Specifically, we examine how AI exposure has evolved from 2010 to 2017 within 4-digit occupations. This nuanced variation within and across narrowly defined occupations serves as a crucial factor in identifying the impact of AI on wages. To estimate the impact of AI exposure on individuals' wages we estimate the following mincer wage regression:

$$\ln(\text{wage})_{iojt} = \beta' \text{Exp}_{\mathbf{ot}} + \phi_t + \theta_o + \gamma' \mathbf{x_{it}} + \lambda' \mathbf{z_{jt}} + \alpha_i + \mu_{J(i,t)} + \epsilon_{iojt} \tag{2}$$

where as in the previous regression (1) workers are indexed by i, occupations by o and plants by j. Subsequently, $\ln(\text{wage})_{ioj,t}$ is the log daily wage of worker i employed by plant j at time t. Note that here the variable *Exp* only refers to changes in the time-varying AI index (DAIOE). Similar to the wage-growth regression, to ensure the robustness of our analysis, we employ an extensive set of controls, including establishment fixed effects. Building on this, we enhance our model by introducing worker fixed effects (α_i) and 4-digit occupation fixed effects. Including establishment controls (size, industry and region) and fixed effects as well as 4-digit occupational fixed effects assist us in controlling for establishment and occupational exposure to other technologies, such as computer and cloud services use, which are known to be correlated, e.g., with establishment size (Acemoglu *et al.*, 2023). The person fixed effect, similar to the AKM person-effect, captures time-invariant characteristics, such as productivity, task performance and skills. This comprehensive approach strengthens our ability to discern and quantify the influence of AI exposure on wage dynamics across different occupational categories.

Table 2 presents results where we exploit time-variation in AI exposure of occupations to estimate the impact on wages. More exposure to AI is positively and statistically significantly linked to a higher wage (Column 1). This benchmark result is, as mentioned, from an estimation where we control for a range of known factors that may confound results in mincer-type regressions. However, adding further or alternative restrictions on the estimations only marginally affects the results. Even when we include 4-digit occupation fixed effects and require the worker to remain in the same occupation and plant as well as being in the sample for eight years, the results are virtually identical in magnitude and they remain statistically significant. In the Appendix, we also control for spell (i.e., worker-plant) fixed effects, and find similar effects (see Table A12). We interpret this finding of AI exposure being associated with an increase in worker wage as either the result of a strong productivity effect of automation or from a reinstatement/augmentation effect from AI.

Table 2: AI Exposure and Wages

	log daily wage					
AI-Exposure$_t$	0.00936	0.0162	0.0166	0.00799	0.0104	0.00949
	(0.00187)	(0.00234)	(0.00250)	(0.00281)	(0.00376)	(0.00402)
Observations	2,433,676	973,680	755,523	1,072,298	343,213	260,488
R-squared	0.913	0.927	0.925	0.893	0.909	0.905
Year fixed effects	yes	yes	yes	yes	yes	yes
Worker Controls	yes	yes	yes	yes	yes	yes
Plant Controls	yes	yes	yes	yes	yes	yes
Worker fixed effects	yes	yes	yes	yes	yes	yes
Plant fixed effects	yes	yes	yes	yes	yes	yes
4-digit occupation fixed effects	yes	yes	yes	yes	yes	yes
Same 4-digit occupation	no	yes	yes	no	yes	yes
Same plant	no	no	yes	no	no	yes
8 years in sample	no	no	no	yes	yes	yes

Notes: The dependent variable in all columns is the log daily wage. Occupational AI exposure is based on the DAIOE measure of Engberg *et al* (2023a). Worker controls include time varying controls, such as experience (-squared, -cubic, - quartic), education, and age (-squared), and indicator variables for same plant and same 4-digit. occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security.

We expect that the differential progress in AI across its subdomains during the study period also heterogeneously affect wages. Major breakthroughs occurred, for example, in image recognition, with AlexNet employing a neural network to win the ImageNet competition in 2012, in strategy games, with AlphaGo defeating the human world champion in the game of Go in 2016, and in machine translation, where major milestones were reached with the introduction of neural machine translation (Google, 2016). Benefiting from the availability of sub-indices of the DAIOE measure, we therefore rerun the wage regression from Table 2, with the results displayed in Table A8. First, we comfortingly notice that the positive and statistically significant association between AI exposure and wages is present also for most sub-indices.[17] Second, we note a relatively large variation in the estimated coefficients. The largest coefficients are to be found for strategy games (0.0924), image recognition (0.694) and translation (0.0422), and the smallest ones for reading comprehension (0.0192) and video games (-0.00824). The results indicate that exposure to different AI-areas is heterogeneously affecting workers' wages, even when meticulously controlling for confounding factors at the worker and plant level. This could be because of differential progress in AI or differential adoption and usefulness of different types of AI.

Analysing the association between AI exposure and wages for different occupational groups reveals distinct patterns, indicating varied outcomes for different segments of the workforce. Notably, among KIBS workers, there is an observed decrease in wages, while for blue-collar workers there is no significant change. These findings speak to the task-replacement effect revealed for KIBS workers in Figure 1. Conversely, non-professional workers, for which we saw an increase in focus on some white collar tasks, witness a wage increase. These are workers where AI exposure is associated with a marked up-skilling (see Figure A14). A more granular analysis reveals that technicians, clerical support and services, and sales agent workers experience a wage increase when their occupation is more exposed to AI progress. In contrast, professionals and operators see a decline in wages. These findings align with the findings of Babina *et al* (2022), suggesting that increased investment in AI contributes to organisational flattening, characterised by fewer middle-management layers. This shift occurs as workers, aided by technology, become more adept at independently solving problems.

[17] See Table A9 for p-values related to Table A8.

4. Concluding remarks

The findings in this paper highlight the complex interplay between technological advancements, work content, and wage dynamics. The extensive exploration of within-occupation changes underscores the nuanced impact of technological advancements. Notably, the stark contrast between occupational AI and robot exposure becomes apparent, manifesting in distinct tasks performed and skill requirements for affected workers.

Our investigation extends beyond the broad assessment of technological exposure and delves into the specific content of work, illustrating how these changes reverberate in individual wage dynamics. While our analysis serves as an initial exploration into the influence of AI on labour market outcomes, it is constrained to the early stages of increasing AI exposure, with a primary focus on wage implications.

Looking ahead, future research endeavours may expand on our findings by examining more recent periods characterised by a rapid acceleration in AI adoption. This exploration could encompass a broader spectrum of outcomes, including potential shifts in employment patterns and unemployment rates, as AI increasingly takes on tasks once performed by humans. By undertaking these future investigations, one would aim to achieve a more comprehensive understanding of the evolving landscape shaped by the pervasive influence of artificial intelligence.

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A Online Appendix

A1. *Task and Skill Changes and within narrowly occupation groups*

Figure A1: *Changes in the task composition within 1-digit occupations*

Notes: The figure illustrates the change in the share of workers that report performing a specific task between 2018 and 2006 within 1-digit occupational groups. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 23,822 individuals from BIBB-BAuA survey waves 2006 and 2018.

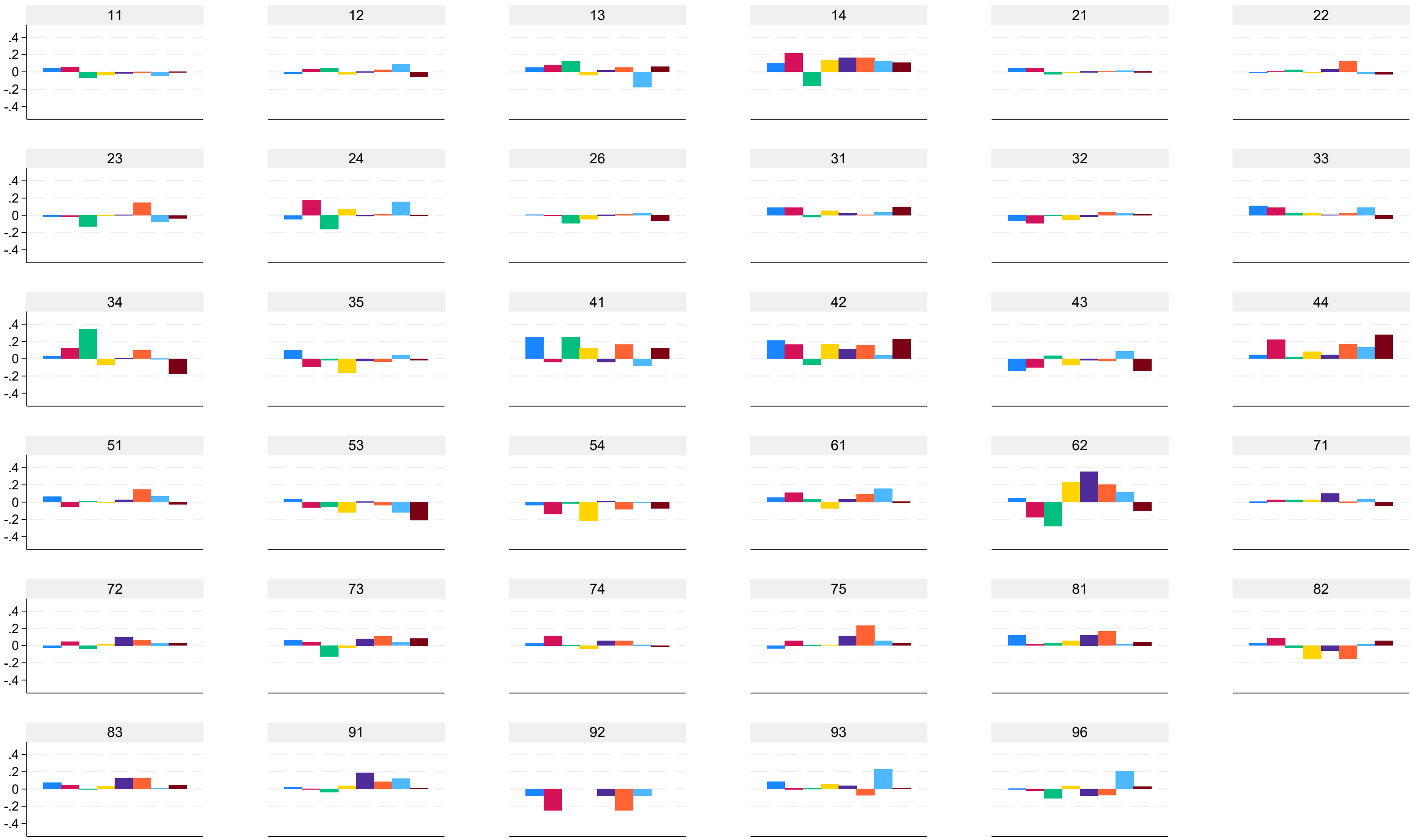
Figure A2: Skill Requirement Changes within 1-digit occupations

Notes: The figure illustrates the change in the share of workers that report a specific skill requirement between 2018 and 2006 within 1-digit occupational groups. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 23,822 individuals from BIBB-BAuA survey waves 2006 and 2018.

Figure A3: Task Composition Changes within 2-digit occupations

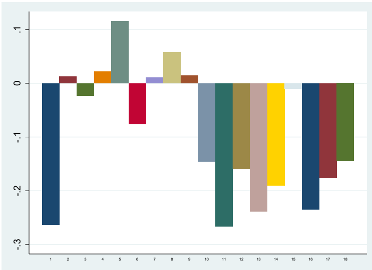
Notes: The figure illustrates the change in the share of workers that report performing a specific task between 2018 and 2006 within 2-digit occupational groups. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 23,822 individuals from BIBB-BAuA survey waves 2006 and 2018.

Figure A4: Skill Requirement Changes within 2-digit occupations

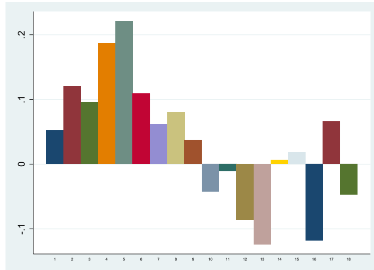


Notes: The figure illustrates the change in the share of workers that report a specific skill requirement between 2018 and 2006 within 2-digit occupational groups. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 23,822 individuals from BIBB-BAuA survey waves 2006 and 2018.

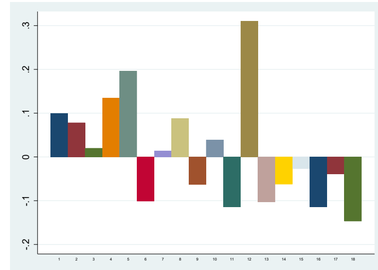
Figure A5: *Changes in the task composition and skill requirements - Inverse sampling weights*



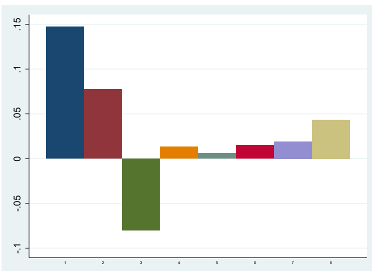
(a) KIBS – Tasks



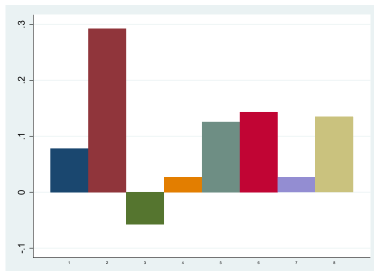
(b) Blue-collar – Tasks



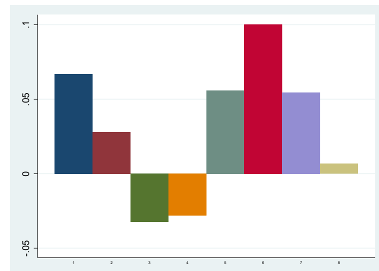
(c) Non-professional – Tasks



(d) KIBS – Skills



(e) Blue-collar – Skills



(f) Non-professional - Skills

Notes: Panel a-c (d-f) illustrates the change in the share of workers that report performing a specific task (report a specific skill requirement) between 2018 and 2006 within the group of KIBS (knowledge intensive business services), Blue-collar, and non-professional occupations. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 14,722 individuals from BIBB-BAuA survey waves 2006 and 2018, using inverse sampling weights.

Figure A6: *Changes in the task composition within 1-digit occupations - Inverse sampling weights*

Notes: The figure illustrates the change in the share of workers that report performing a specific task between 2018 and 2006 within 1-digit occupational groups. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 23,822 individuals from BIBB-BAuA survey waves 2006 and 2018, using inverse sampling weights

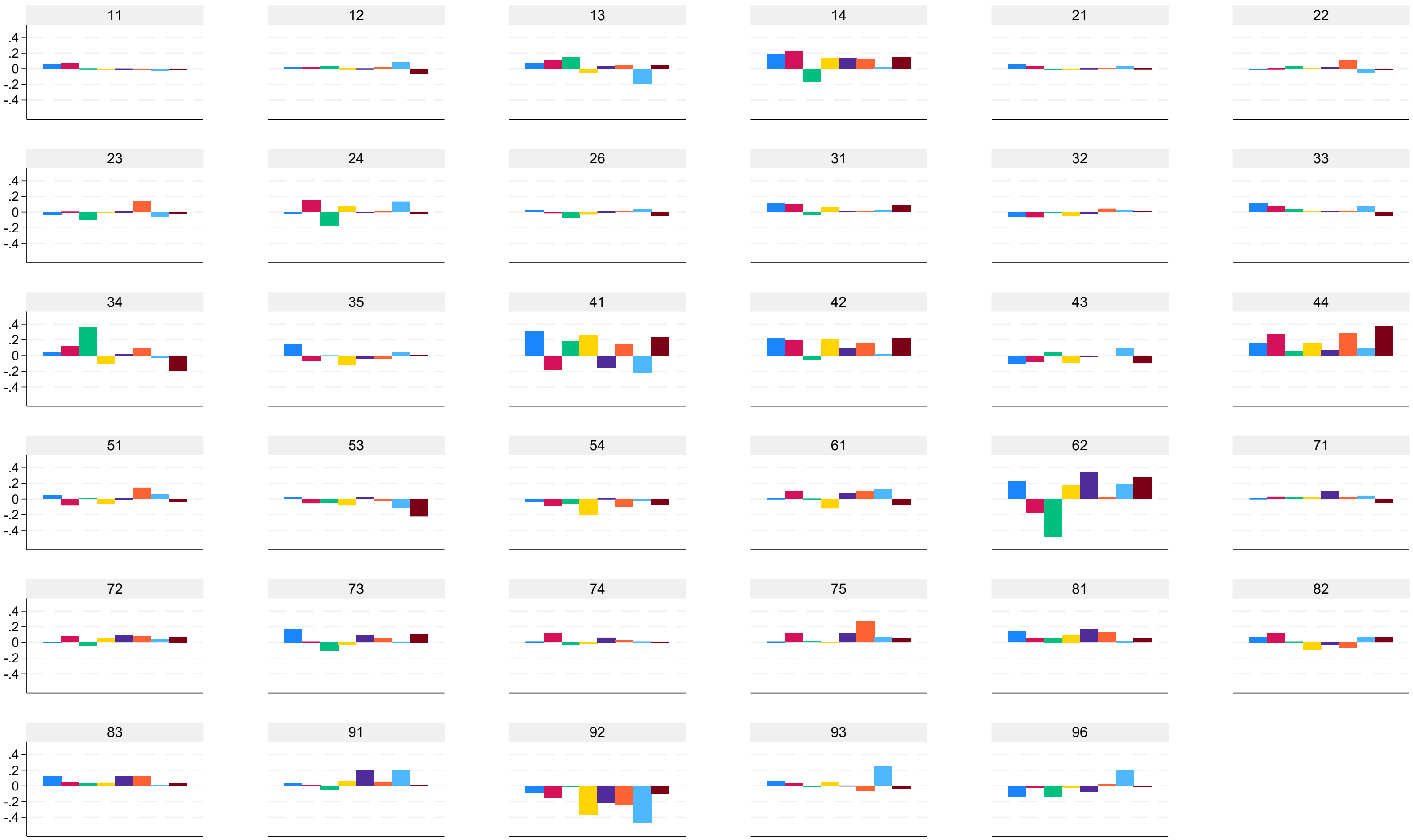
Figure A7: Skill Requirement Changes within 1-digit occupations - Inverse sampling weights

Notes: The figure illustrates the change in the share of workers that report a specific skill requirement between 2018 and 2006 within 1-digit occupational groups. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 23,822 individuals from BIBB-BAuA survey waves 2006 and 2018, using inverse sampling weights.

Figure A8: Task Composition Changes within 2-digit occupations - Inverse sampling weights

Notes: The figure illustrates the change in the share of workers that report performing a specific task between 2018 and 2006 within 2-digit occupational groups. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 23,822 individuals from BIBB-BAuA survey waves 2006 and 2018, using inverse sampling weights.

Figure A9: Skill Requirement Changes within 2-digit occupations - Inverse sampling weights



Notes: The figure illustrates the change in the share of workers that report a specific skill requirement between 2018 and 2006 within 2-digit occupational groups. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on 23,822 individuals from BIBB-BAuA survey waves 2006 and 2018, using inverse sampling weights.

A2. Descriptive and Summary Statistics on BIBB-BAuA data

Table A1: Frequency of Task Performance and Skill Requirements

Task Performance	
1. Program a Computer	0.0971
2. Computer use	0.8622
3. Developing, researching, constructing	0.3619
4. Gathering information, researching, documenting	0.8526
5. Organize, Plan, Prepare (others' work)	0.7129
6. Purchase, Procure, Sell	0.4166
7. Consult and Inform	0.8794
8. Train, Teach, Instruct, Educate	0.6027
9. Advertise, Promote, Conduct Marketing and PR	0.3851
10. Protecting, guarding, monitoring, reglating traffic	0.3769
11. Repair, Maintain	0.4181
12. Entertain, Accommodate, Prepare Foods	0.1940
13. Nurse, Look After, Cure	0.2529
14. Cleaning, waste disposal, recycling	0.4674
15. Measure, Inspect, Control Quality	0.7025
16. Manufacture, Produce Goods	0.2227
17. Transport, Store, Dispatch	0.4996
18. Oversee, Control Machinery and Techn. Processes	0.4264
Average number of tasks	8.7312
Skill Requirements	
1. Legal knowledge	0.6799
2. Project management	0.5031
3. Medical or nursing field	0.3116
4. Mathematics, calculus, statistics	0.7724
5. German, written expression, spelling	0.9267
6. PC application programs	0.8216
7. Technical knowledge	0.7086
8. Commercial or business knowledge	0.5878

Notes: The table reports the share of workers that perform a specific task in their job and report specific skill requirements in their job. The table is based on survey response from 35,191 individuals.
Source: BIBB-BAuA waves 2006, 2012 and 2018.

Table A2: Summary statistics for regression sample on Section 2.2.

Variable	Mean	Std. dev.	Min	Max
Log hourly wage	2.7909	0.4813	0.3448	5.7793
Education in years	13.0626	2.2893	8	18
Age	41.8435	9.8114	19	65
Experience	23.7809	10.2312	0	50
Indic.: Married	0.5265	0.4993	0	1
Indic.: Parttime	0.1102	0.3132	0	1
Indic.: Female	0.4621	0.4986	0	1
Indic.: Type of Employment	1.7670	0.5601	1	3

Notes: The table reports summary statistics on individual outcomes for the sample used to generate figures in Section 2.2.. The sample is based on 11,125 individuals. Hourly gross wage is computed from information on the monthly gross wage and weekly working hours. Education is measured in years of schooling and years at university (excluding PhD). Work experience is measured in years in employment using the workers age information and the years of education incl. training. The type of employment differentiates between worker, salaried employee, or civil servant.
Source: BIBB-BAuA waves 2006.

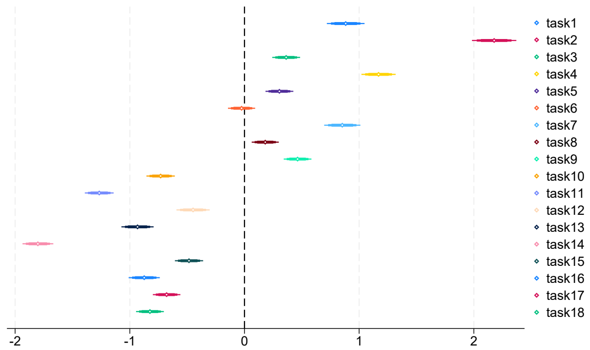
A3. Descriptive and Summary Statistics on SIAB samples

Table A3: Summary statistics for regression samples on Section 3.

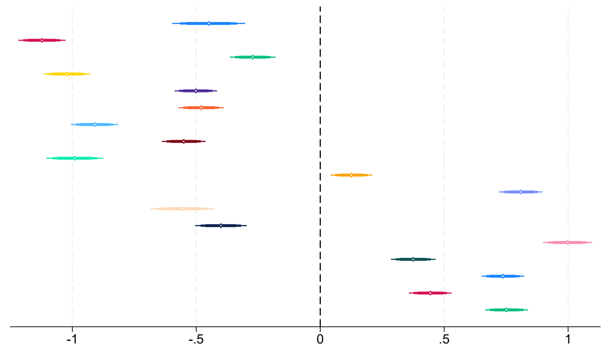
Variable	Mean	Std. dev.	Min	Max
Log daily wage	4.7386	0.6957	2.6059	7.7855
Age	41.9219	10.6162	20	60
Experience	19.6219	9.8562	0	42
Indic.: Migrant	0.0724	0.2592	0	1
Indic.: Female	0.2961	0.4565	0	1
Indic.: Qual. for lower sec. school	0.60038	0.4898	0	1
Indic.: Qual. for FH or University w/o vocational qual.	0.01000	0.0993	0	1
Indic.: Qual. for FH or University with vocational qual.	0.1294	0.3357	0	1
Indic.: University of Applied Sciences (FH)	0.0303	0.1715	0	1
Indic.: University	0.1799	0.3841	0	1
Indic.: Switch plant	0.4010	0.4901	0	1
Indic.: Switch 4-digit occupation	0.6020	0.4895	0	1
Indic.: Rightcensored wage	0.1160	0.3202	0	1
Log plant employment	1.6017	0.4952	0	2.0794

Notes: The table reports summary statistics on individual outcomes for the sample used in regressions in Section 3.. Daily wage is based on information in the data (daily wage/daily benefit). As wages above the upper earnings limit for statutory pension insurance are right-censored, we replace right-censored wages with imputed wages, by following the methodology in Card *et al* (2013). Age is computed from information on the year of birth. Information on education can be classified into The number are based on 2,508,165 observations.
Source: SIAB 2010 to 2017.

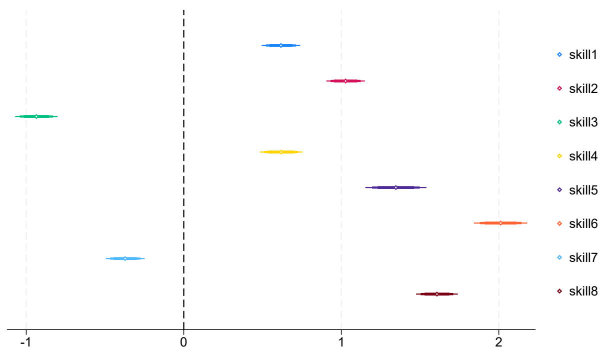
Figure A10: *Task, skills, and Exposure to Technology - No Controls*



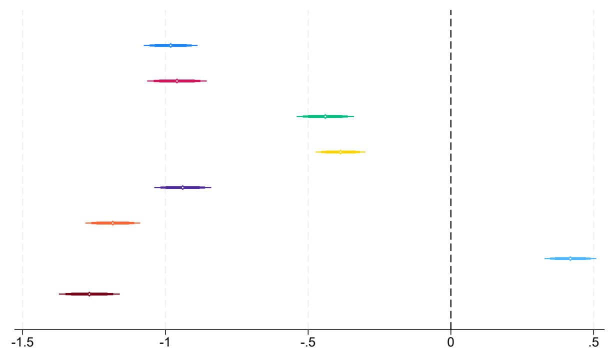
(a) Tasks & AI-Exposure



(b) Tasks & Robot-Exposure



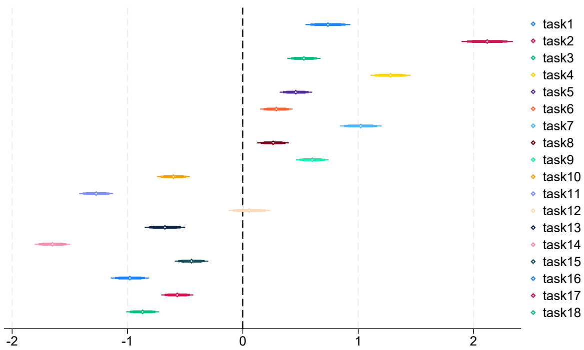
(c) Skills & AI-Exposure



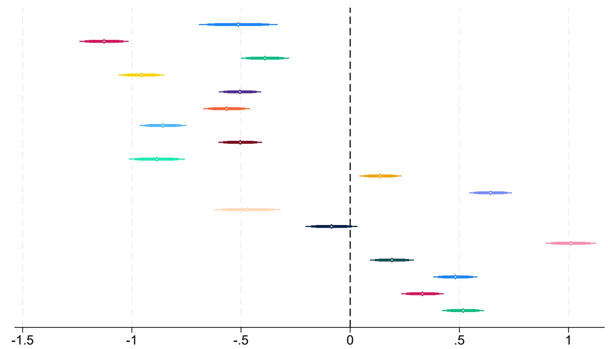
(d) Skills & Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) from estimating probit regressions on the probability of 18 task performance and 8 skill requirement indicators, without controls. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 11,125 individuals from the BIBB-BAuA survey wave 2006. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

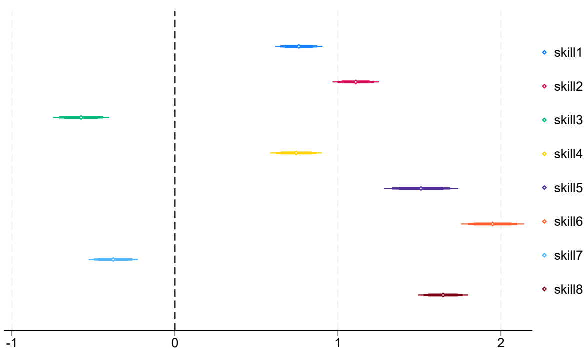
Figure A11: *Task, skills, and Exposure to Technology - Basic controls*



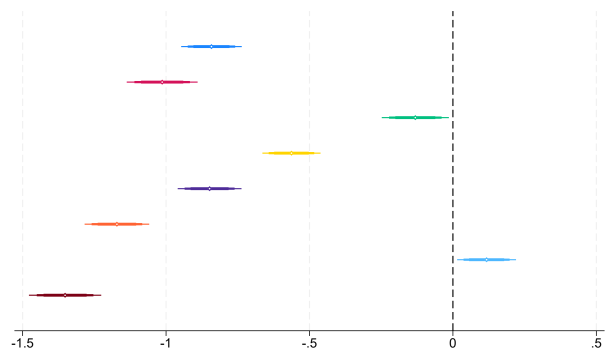
(a) Tasks & AI-Exposure



(b) Tasks & Robot-Exposure



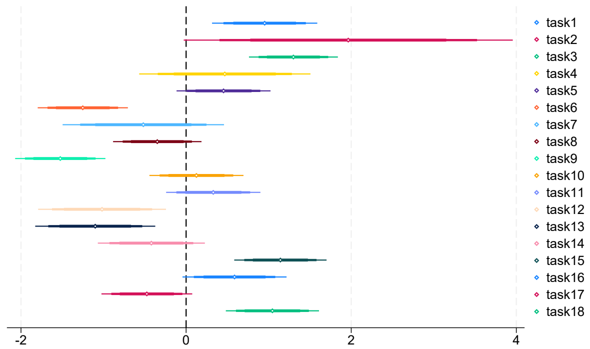
(c) Skills & AI-Exposure



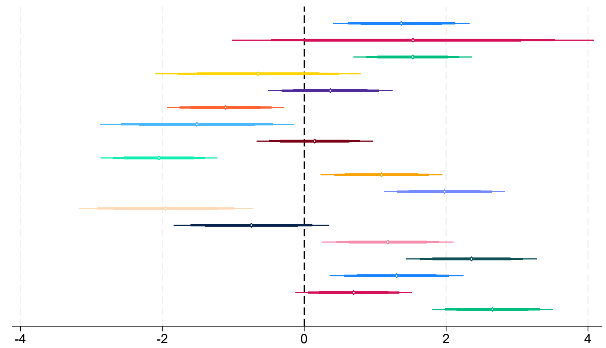
(d) Skills & Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) from estimating probit regressions on the probability of 18 task performance and 8 skill requirement indicators, controlling for industry, region and plant-size. Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 11,125 individuals from the BIBB-BAuA survey wave 2006. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

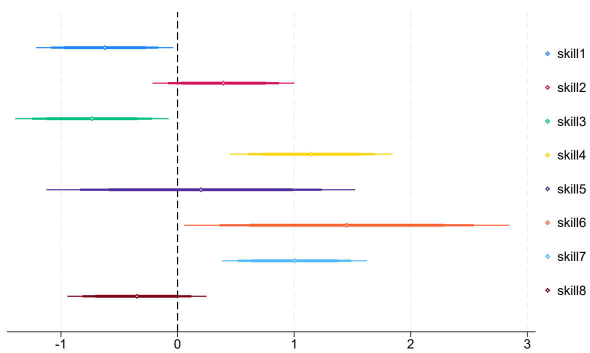
Figure A12: *Task, skills, and Exposure to Technology - KIBS*



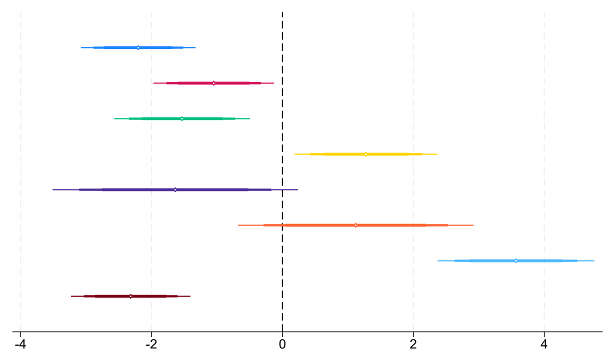
(a) Tasks & AI-Exposure



(b) Tasks & Robot-Exposure



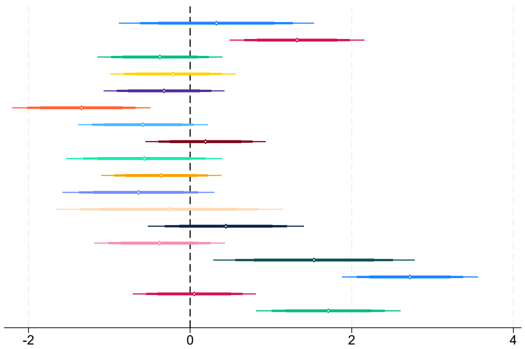
(c) Skills & AI-Exposure



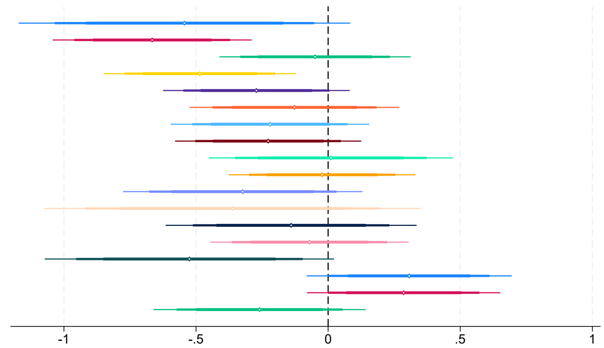
(d) Skills & Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) from estimating probit regressions on the probability of 18 task performance and 8 skill requirement indicators, controlling for industry, region, plant-size and worker controls (incl. log hourly wage, education, age (-squared), experience (-squared, -cubic, - quartic), married, part-time, gender, and type of employment). Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 2,287 individuals from the BIBB-BAuA survey wave 2006 working in KIBS occupations. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

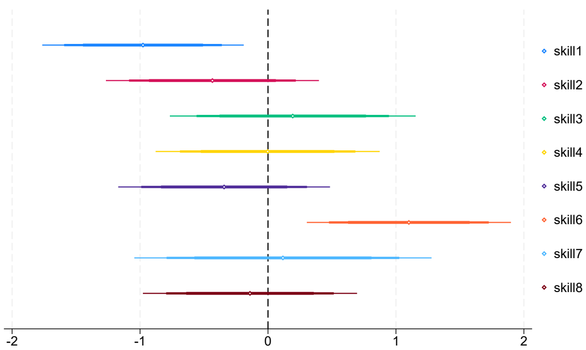
Figure A13: *Task, skills, and Exposure to Technology - Blue-collar*



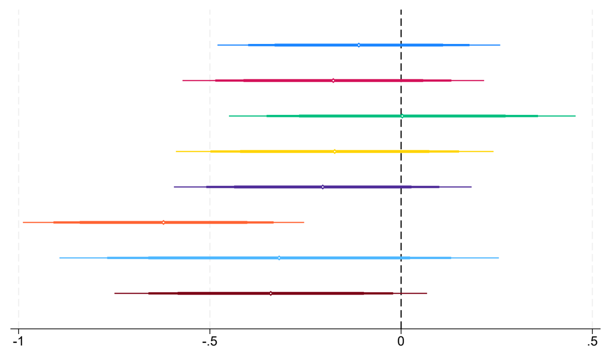
(a) Tasks & AI-Exposure



(b) Tasks & Robot-Exposure



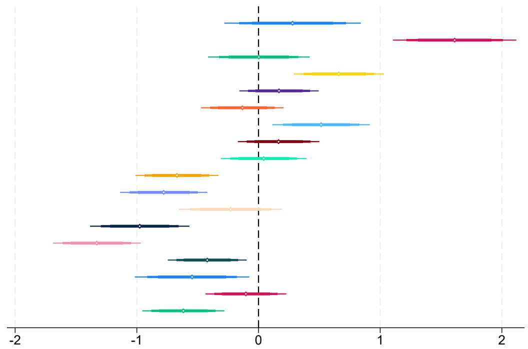
(c) Skills & AI-Exposure



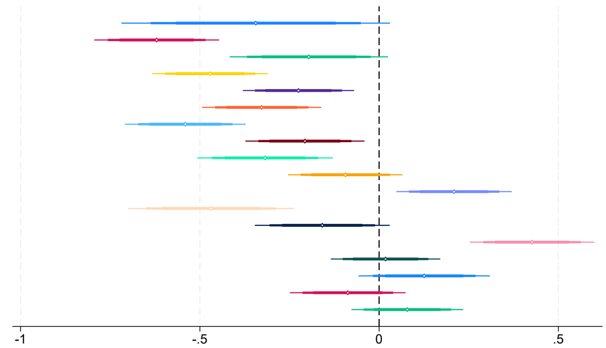
(d) Skills & Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) from estimating probit regressions on the probability of 18 task performance and 8 skill requirement indicators, controlling for industry, region, plant-size and worker controls (incl. log hourly wage, education, age (-squared), experience (-squared, -cubic, - quartic), married, part-time, gender, and type of employment). Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 2,440 individuals from the BIBB-BAuA survey wave 2006 working in Blue-collar occupations. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

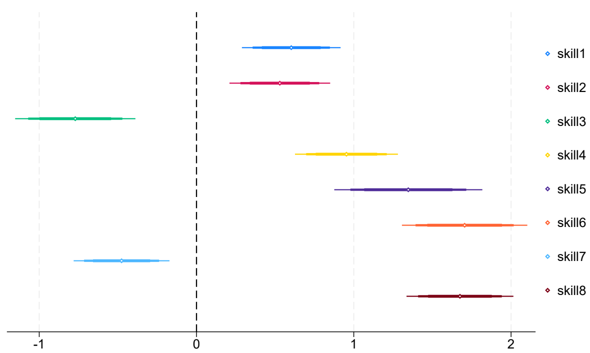
Figure A14: *Task, skills, and Exposure to Technology - Non-professionals*



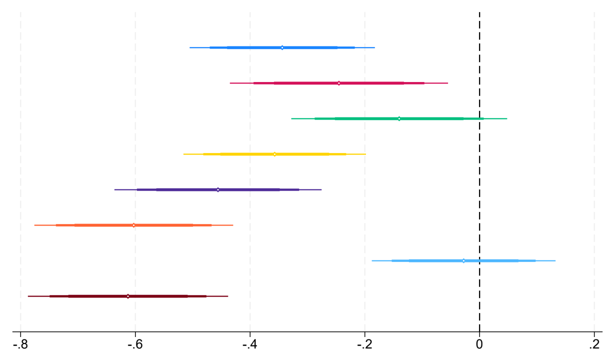
(a) Tasks & AI-Exposure



(b) Tasks & Robot-Exposure



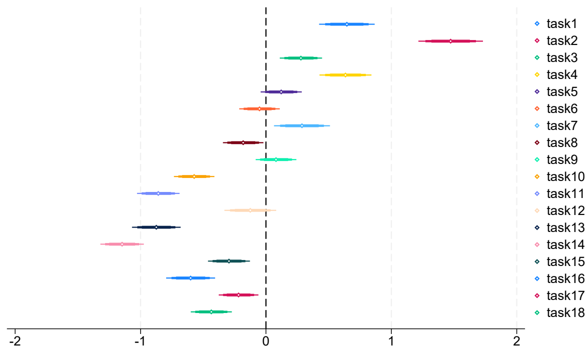
(c) Skills & AI-Exposure



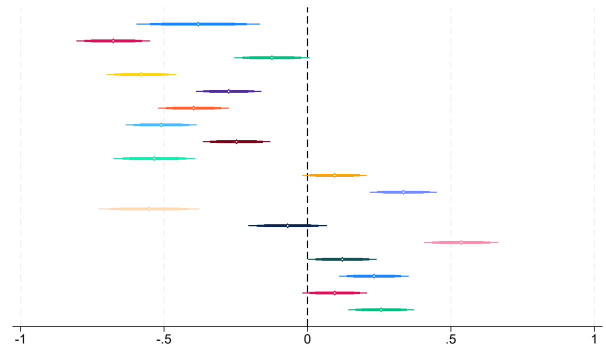
(d) Skills & Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) from estimating probit regressions on the probability of 18 task performance and 8 skill requirement indicators, controlling for industry, region, plant-size and worker controls (incl. log hourly wage, education, age (-squared), experience (-squared, -cubic, - quartic), married, part-time, gender, and type of employment). Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 2,827 individuals from the BIBB-BAuA survey wave 2006 working in non-professional occupations. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

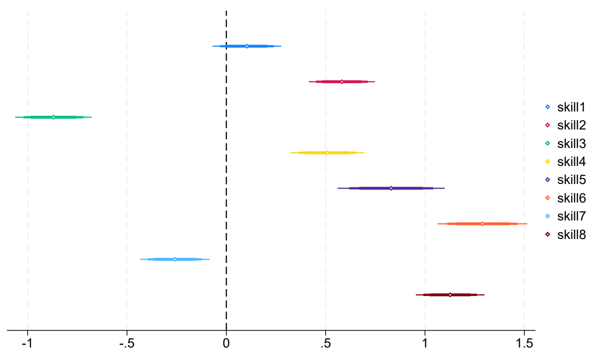
Figure A15: *Task, skills, and Exposure to Technology - Controlling for Software Exposure*



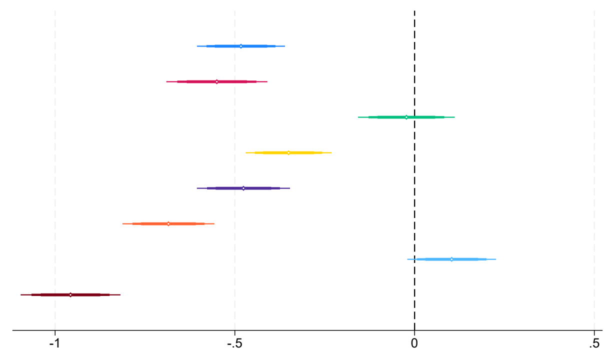
(a) Tasks & AI-Exposure



(b) Tasks & Robot-Exposure



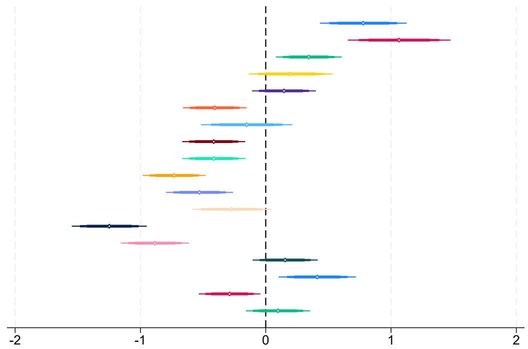
(c) Skills & AI-Exposure



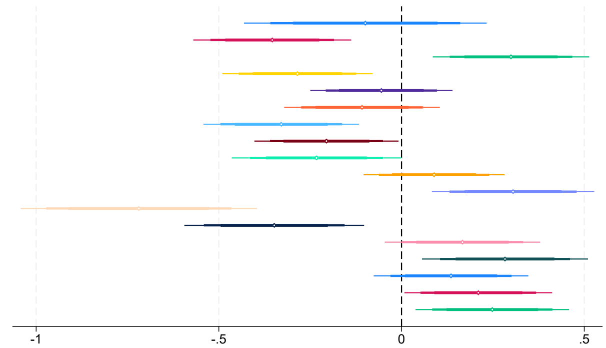
(d) Skills & Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) when estimating probit regressions on the probability for 18 task performance and 8 skill requirement indicators, controlling for industry, region, plant-size and worker controls (log hourly wage, education, age (-squared), experience (-squared, -cuibic, - quartic), married, part-time, gender, and type of employment. Regression on AI-exposure (Panel a and c) also includes occupational software exposure measure. Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 11,125 individuals from the BIBB-BAuA survey wave 2006. Occupational AI exposure is based on FRS 18 index from 2017. Occupational robot exposure and software exposure is based on the index from Webb (2020).

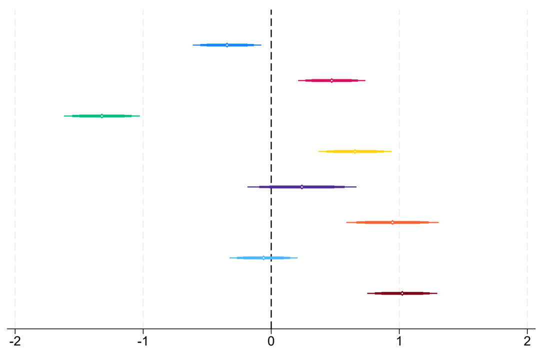
Figure A16: *Task, skills, and Exposure to Technology - 1-digit occupation FE*



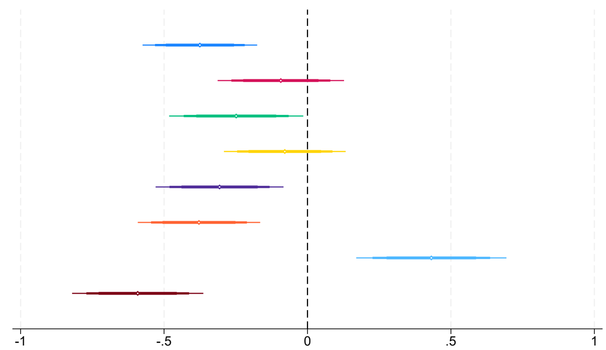
(a) Tasks & AI-Exposure



(b) Tasks & Robot-Exposure



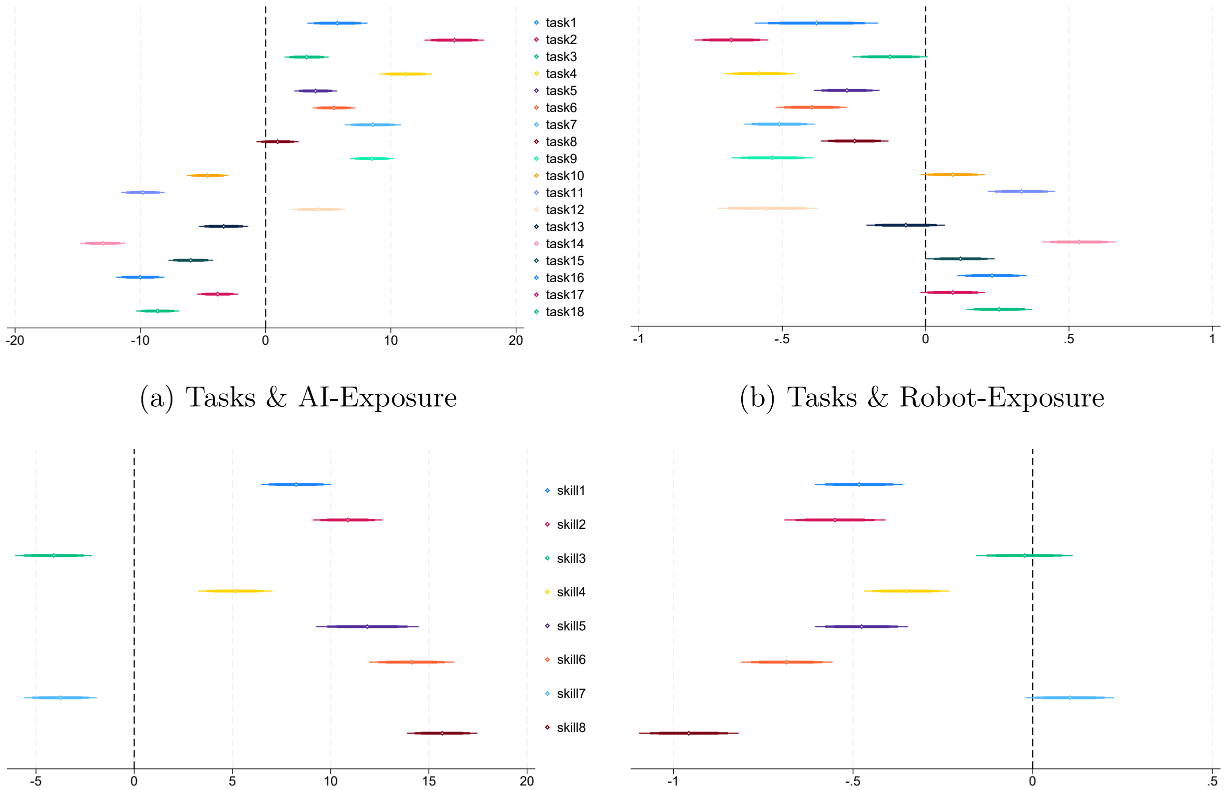
(c) Skills & AI-Exposure



(d) Skills & Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) when estimating probit regressions on the probability for 18 task performance and 8 skill requirement indicators, controlling for industry, region, plant-size and worker controls (log hourly wage, education, age (-squared), experience (-squared, -cuibic, - quartic), married, part-time, gender, and type of employment. Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 11,125 individuals from the BIBB-BAuA survey wave 2006. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

Figure A17: *Task, skills, and Exposure to Technology - FRS 18 index*



(a) Tasks & AI-Exposure

(b) Tasks & Robot-Exposure

(c) Skills & AI-Exposure

(d) Skills & Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a and c) or robot exposure (Panel b and d) when estimating probit regressions on the probability for 18 task performance and 8 skill requirement indicators, controlling for industry, region, plant-size and worker controls (log hourly wage, education, age (-squared), experience (-squared, -cuibic, - quartic), married, part-time, gender, and type of employment. Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals. The 18 different tasks are: 1) Program a Computer; 2) Computer use; 3) Developing, researching, constructing; 4) Gathering information, researching, documenting; 5) Organise, Plan, Prepare (others' work); 6) Purchase, Procure, Sell; 7) Consult & Inform; 8) Train, Teach, Instruct, Educate; 9) Advertise, Promote, Conduct Marketing & PR; 10) Protecting, guarding, monitoring, regulating traffic; 11) Repair, Maintain; 12) Entertain, Accommodate, Prepare Foods; 13) Nurse, Look After, Cure; 14) Cleaning, waste disposal, recycling; 15) Measure, Inspect, Control Quality; 16) Manufacture, Produce Goods; 17) Transport, Store, Dispatch; 18) Oversee, Control Machinery & Techn. Processes. The 8 different skill requirements are: 1) Legal knowledge; 2) Knowledge of project management; 3) Knowledge in the medical or nursing field; 4) Knowledge in mathematics, calculus, statistics; 5) Knowledge of German, written expression, spelling; 6) Knowledge of PC application programs; 7) Technical knowledge; 8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 11,125 individuals from the BIBB-BAuA survey wave 2006. Occupational AI exposure is based on FRS 18 index from 2017. Occupational robot exposure is based on the index from Webb (2020).

Table A4: AI Exposure, Robot Exposure, and Average Wage Growth

	Average yearly log wage change between 2010 and 2017					
AI-Exposure$_{2017}$	0.00406	0.00570	0.00265	0.00406	0.00570	0.00265
	(0.000675)	(0.00107)	(0.00210)	(0.00135)	(0.00195)	(0.00231)
Robot-Exposure$_{2017}$	-0.00201	-0.00185	-0.00200	-0.00201	-0.00185	-0.00200
	(0.000459)	(0.000784)	(0.00201)	(0.000901)	(0.00107)	(0.00185)
Observations	311287	197547	197547	311287	197547	197547
R-squared	0.090	0.303	0.305	0.09o	0.303	0.305
Worker Controls	yes	yes	yes	yes	yes	yes
Plant Controls	yes	yes	yes	yes	yes	yes
Worker AKM effect	yes	yes	yes	yes	yes	yes
Plant fixed effects	no	yes	yes	no	yes	yes
3-digit-occupation fixed effects	no	no	yes	no	no	yes
Clustered-SE at 4-digit occupation	no	no	no	yes	yes	yes

Notes: The dependent variable in all columns is the average yearly change in the log daily wage. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020). Worker controls include controls for gender, experience (-squared, -cubic, - quartic), age (-squared), education, migrant, indicator variables for same plant and same 4-digit occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security.

Table A5: AI Exposure, Robot Exposure, and Average Wage Growth - Same Occupation

	Average yearly log wage change between 2010 and 2017					
AI-Exposure$_{2017}$	0.00360	0.00564	0.00415	0.00360	0.00564	0.00415
	(0.000713)	(0.00118)	(0.00233)	(0.000713)	(0.00118)	(0.00233)
Robot-Exposure$_{2017}$	-0.000704	-0.000265	-0.00140	-0.000704	-0.000265	-0.00140
	(0.000486)	(0.000869)	(0.00223)	(0.000666)	(0.00101)	(0.00202)
Observations	306764	194336	194336	306764	194336	194336
R-squared	0.055	0.248	0.250	0.055	0.248	0.250
Worker Controls	yes	yes	yes	yes	yes	yes
Plant Controls	yes	yes	yes	yes	yes	yes
Worker AKM effect	yes	yes	yes	yes	yes	yes
Plant fixed effects	no	yes	yes	no	yes	yes
3-digit occupation fixed effects	no	no	yes	no	no	yes
Clustered-SE at 4-digit occupation	no	no	no	yes	yes	yes

Notes: The dependent variable in all columns is the average yearly change in the log daily wage. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020). Worker controls include controls for gender, experience (-squared, -cubic, - quartic), age (-squared), education, migrant, indicator variables for same plant and same 4-digit occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security, which remain in the same 4-digit occupation.

Table A6: AI Exposure, Robot Exposure, and Average Wage Growth - Same Occupation and Plant

	Average yearly log wage change between 2010 and 2017					
AI-Exposure$_{2017}$	0.00384	0.00644	0.00541	0.00384	0.00644	0.00541
	(0.000741)	(0.00125)	(0.00246)	(0.00141)	(0.00188)	(0.00312)
Robot-Exposure$_{2017}$	-0.000525	-0.0000520	-0.00196	-0.000525	-0.0000520	-0.00196
	(0.000506)	(0.000918)	(0.00236)	(0.000650)	(0.000993)	(0.00193)
Observations	303334	192053	192053	303334	192053	192053
R-squared	0.46	0.236	0.238	0.46	0.236	0.238
Worker Controls	yes	yes	yes	yes	yes	yes
Plant Controls	yes	yes	yes	yes	yes	yes
Worker AKM effect	yes	yes	yes	yes	yes	yes
Plant fixed effects	no	yes	yes	no	yes	yes
3-digit occupation fixed effects	no	no	yes	no	no	yes
Clustered-SE at 4-digit occupation	no	no	no	yes	yes	yes

Notes: The dependent variable in all columns is the average yearly change in the log daily wage. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020). Worker controls include controls for gender, experience (-squared, -cubic, - quartic), age (-squared), education, migrant, indicator variables for same plant and same 4-digit occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security, which remain in the same 4-digit occupation and same plant.

Table A7: AI Exposure, Robot Exposure, and Wage Growth - AI measure from Felten *et al.* (2018)

	Change in log daily wage between 2010 and 2017					
AI-Exposure$_{2017}$	0.414	0.595	0.748	0.414	0.595	0.748
	(0.0564)	(0.107)	(0.267)	(0.116)	(0.194)	(0.281)
Robot-Exposure$_{2017}$	-0.00798	-0.00848	-0.0124	-0.00798	-0.00848	-0.0124
	(0.00368)	(0.00748)	(0.0182)	(0.00551)	(0.00890)	(0.0160)
Observations	136,296	76,324	76,322	136,296	76,324	76,322
R-squared	0.123	0.314	0.318	0.123	0.314	0.318
Worker Controls	yes	yes	yes	yes	yes	yes
Plant Controls	yes	yes	yes	yes	yes	yes
Worker AKM effect	yes	yes	yes	yes	yes	yes
Plant fixed effects	no	yes	yes	no	yes	yes
3-digit occupation fixed effects	no	no	yes	no	no	yes
Clustered-SE at 4-digit occupation	no	no	no	yes	yes	yes

Notes: The dependent variable in all columns is the difference in the log daily wage between 2017 and 2010. Occupational AI exposure is based on the AI measure from (Felten *et al.*, 2018). Occupational robot exposure is based on the index from Webb (2020). Worker controls include controls for gender, experience (-squared, -cubic, - quartic), age (-squared), education, migrant, indicator variables for same plant and same 4-digit occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security.

Table A8: AI Subfield Exposure and Wages

	log daily wage		
AI-stratgames$_t$	0.0947	0.0895	0.0924
	(0.0574)	(0.0574)	(0.0573)
AI-videogames$_t$	-0.0101	-0.00714	-0.00824
	(0.0199)	(0.0199)	(0.0199)
AI-imgrec$_t$	0.0756	0.0696	0.0694
	(0.0349)	(0.0349)	(0.0439)
AI-imgcompr$_t$	0.0287	0.0262	0.0265
	(0.0130)	(0.0130)	(0.0130)
AI-readcompr$_t$	0.0201	0.0185	0.0192
	(0.00968)	(0.00968)	(0.00967)
AI-lngmod$_t$	0.0326	0.0296	0.0307
	(0.0162)	(0.0162)	(0.0162)
AI-translat$_t$	0.0450	0.0407	0.0422
	(0.0208)	(0.0208)	(0.0208)
AI-speechrec$_t$	0.0233	0.0210	0.0217
	(0.0111)	(0.0111)	(0.0110)
Observations	559,686	539,920	528,530
R-squared	0.950	0.949	0.948
Year fixed effects	yes	yes	yes
Worker Controls	yes	yes	yes
Plant Controls	yes	yes	yes
Worker fixed effects	yes	yes	yes
Plant fixed effects	yes	yes	yes
4-digit occupation fixed effects	yes	yes	yes
Same 4-digit occupation	no	yes	yes
Same plant	no	no	yes

Notes: The dependent variable in all columns is the log daily wage. Occupational AI exposure is based on DAOIE index and its respective subfields Engberg *et al* (2023a). Worker controls include time varying controls, such as experience (-squared, -cubic, - quartic), education, and age (-squared), and indicator variables for same plant and same 4-digit. occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security.

Table A9: AI Subfield Exposure and Wages – P-values

	log daily wage		
AI-stratgames$_t$	0.099	0.119	0.107
AI-videogames$_t$	0.611	0.720	0.679
AI-imgrec$_t$	0.030	0.046	0.047
AI-imgcompr$_t$	0.027	0.044	0.041
AI-readcompr$_t$	0.038	0.056	0.047
AI-lngmod$_t$	0.044	0.068	0.058
AI-translat$_t$	0.031	0.051	0.042
AI-speechrec$_t$	0.035	0.058	0.049
Observations	559,686	539,920	528,530
R-squared	0.950	0.949	0.948
Year fixed effects	yes	yes	yes
Worker Controls	yes	yes	yes
Plant Controls	yes	yes	yes
Worker fixed effects	yes	yes	yes
Plant fixed effects	yes	yes	yes
4-digit occupation fixed effects	yes	yes	yes
Same 4-digit occupation	no	yes	yes
Same plant	no	no	yes

Notes: The table provides p-values to estimates presented in Table A8. The dependent variable in all columns is the log daily wage. Occupational AI exposure is based on DAOIE index and its respective subfields Engberg *et al* (2023a). Worker controls include time varying controls, such as experience (-squared, -cubic, -quartic), education, and age (-squared), and indicator variables for same plant and same 4-digit. occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security.

Table A10: AI Exposure and Wages for different occupation groups

	log daily wage					
Occupation group	KIBS		Blue-collar		Non-professional	
AI-Exposure$_t$	-0.0244	-0.0541	0.00677	-0.000755	0.0127	0.0369
	(0.00964)	(0.0180)	(0.00309)	(0.00379)	(0.00224)	(0.00345)
Observations	362,302	89,538	632,890	231,886	813,456	304,736
R-squared	0.858	0.873	0.946	0.948	0.938	0.936
Year fixed effects	yes	yes	yes	yes	yes	yes
Worker Controls	yes	yes	yes	yes	yes	yes
Plant Controls	yes	yes	yes	yes	yes	yes
Worker fixed effects	yes	yes	yes	yes	yes	yes
Plant fixed effects	yes	yes	yes	yes	yes	yes
4-digit occupation fixed effects	yes	yes	yes	yes	yes	yes
Same occupation & plant	no	yes	no	yes	no	yes

Notes: The dependent variable in all columns is the log daily wage. Occupational AI exposure is based on the DAIOE measure of Engberg *et al* (2023a). Worker controls include time varying controls, such as experience (-squared, -cubic, - quartic), education, and age (-squared), and indicator variables for same plant and same 4-digit. occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security.

Table A11: AI Exposure and Wages for different 1-digit occupation groups

	log daily wage					
1-digit ISCO-08 group	Managers		Professionals		Technicans	
AI-Exposure$_t$	-0.00561	0.0719	-0.0300	-0.0362	0.0184	0.0177
	(0.0402)	(0.140)	(0.00699)	(0.00943)	(0.00529)	(0.00911)
Observations	102,187	6,882	358,3520	155,080	398,111	96,935
R-squared	0.811	0.887	0.855	0.873	0.892	0.903
1-digit ISCO-08 group	Clerical Support		Service & Sales		Agricultural	
AI-Exposure$_t$	0.0527	0.129	0.105	0.128	-0.0214	-0.138
	(0.00625)	(0.00943)	(0.00771)	(0.0105)	(0.0459)	(0.115)
Observations	374,454	146,172	194,789	86,685	18,320	7,184
R-squared	0.919	0.918	0.949	0.943	0.946	0.947
1-digit ISCO-08 group	Craft & Trade		Operators		Elementary Occupations	
AI-Exposure$_t$	0.00202	-0.00573	-0.0434	-0.0549	0.00805	0.0253
	(0.00336)	(0.00398)	(0.00825)	(0.0136)	(0.0117)	(0.0220)
Observations	451,562	175,244	280,074	95,849	97,368	25,476
R-squared	0.941	0.940	0.957	0.959	0.959	0.955
Year fixed effects	yes	yes	yes	yes	yes	yes
Worker Controls	yes	yes	yes	yes	yes	yes
Plant Controls	yes	yes	yes	yes	yes	yes
Worker fixed effects	yes	yes	yes	yes	yes	yes
Plant fixed effects	yes	yes	yes	yes	yes	yes
4-digit occupation fixed effects	yes	yes	yes	yes	yes	yes
Same occupation & plant	no	yes	no	yes	no	yes

Notes: The dependent variable in all columns is the log daily wage. Occupational AI exposure is based on the DAIOE measure of Engberg *et al* (2023a). Worker controls include time varying controls, such as experience (-squared, -cubic, - quartic), education, and age (-squared), and indicator variables for same plant and same 4-digit. occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security.

Table A12: AI Exposure and Wages - Spell-Fixed Effects

	log daily wage			
AI-Exposure$_t$	0.00561	0.0162	0.00675	0.0102
	(0.00190)	(0.00234)	(0.00283)	(0.00376)
Observations	2,325,778	973,680	1,057,161	341,436
R-squared	0.925	0.893	0.894	0.909
Year fixed effects	yes	yes	yes	yes
Worker Controls	yes	yes	yes	yes
Plant Controls	yes	yes	yes	yes
Worker-Plant fixed effects	yes	yes	yes	yes
4-digit occupation fixed effects	yes	yes	yes	yes
Same 4-digit occupation	no	yes	no	yes
8 years in sample	no	no	yes	yes

Notes: The dependent variable in all columns is the log daily wage. Occupational AI exposure is based on the DAIOE measure of Engberg *et al* (2023a). Worker controls include time varying controls, such as experience (-squared, -cubic, - quartic), education, and age (-squared), and indicator variables for same plant and same 4-digit. occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects.
Source: SIAB 2010-2017 restricted to full-time workers, liable to social security.