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ABSTRACT

AI, Task Changes in Jobs, and Worker Reallocation*

How does Artificial Intelligence (AI) affect the task content of work, and how do workers adjust to the diffusion of AI in the economy? To answer these important questions, we combine novel patent-based measures of AI and robot exposure with individual survey data on tasks performed on the job and administrative data on worker careers. Like prior studies, we find that robots have reduced routine tasks. In sharp contrast, AI has reduced non-routine abstract tasks like information gathering and increased the demand for 'high-level' routine tasks like monitoring processes. These task shifts mainly occur within detailed occupations and become stronger over time. While displacement effects are small, workers have responded by switching jobs, often to less exposed industries. We also document that low-skilled workers suffer some wage losses, while high-skilled incumbent workers experience wage gains.

JEL Classification: J23, J24, J31, J62

Keywords: Artificial Intelligence, tasks, skills, reallocation, robots, patents

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1 Introduction

Artificial Intelligence (AI) has seen stunning progress over the past years expanding the domains in which AI is potentially applicable (Maslej et al., 2024). Its vast potential has sparked concerns that AI could displace many workers and sharply increase inequality. An emerging literature has investigated the labor market effects of AI, focusing on worker employment and wages (e.g., Acemoglu et al., 2022, Alekseeva et al., 2021, Bloom et al., 2024, Brynjolfsson et al., 2018, Bonfiglioli et al., 2023, Engberg et al., 2024, Felten et al., 2018, Mann and Püttmann, 2023, Webb, 2020). Most studies find no evidence for job displacement and a modest impact on wages or inequality among workers.

Little is known about how AI changes jobs beyond displacement and whether and how workers have adjusted to any such changes. This gap is all the more surprising because the theoretical literature has moved beyond the notion that technological change raises marginal productivities of inputs to include the idea that machines can take over some tasks traditionally performed by workers (Acemoglu and Autor, 2011, Acemoglu and Restrepo, 2019, Acemoglu et al., 2024, Autor et al., 2024). In these task-based models, workers then have to switch to other, possibly complementary tasks that are not yet automated, or perform new tasks that emerge in response to the new technology. As a result, the task content of jobs exposed to the new technology will change. Such a shift might be accompanied by job displacement, but it needs not be. Moreover, technological change might also change who performs a task if workers differ in their comparative advantage (Acemoglu and Restrepo, 2018). Technological advances like robots could perform 'routine tasks' that can be codified into simple rules. AI, in contrast, does not need humans to program every step of their work but can apply machine learning techniques without following human logic (Brynjolfsson et al., 2018). Many therefore believe that AI has the capability to perform 'non-routine' tasks that require tacit knowledge (Felten et al., 2018). The consequences of observed task shifts for employment, worker productivity, and wages then depend crucially on the type of tasks that get automated; whether workers can switch to complementary tasks; and how non-automated tasks are assigned to different types of workers.[1]

In this paper, we analyze how AI has affected the task content of jobs in Germany, and compare it to the impact of robots. In particular, we study whether workers exposed to AI are less likely

[1] A few recent field experiments show that generative AI has the potential to increase worker productivity (see Brynjolfsson et al. (2023) for call centers, Hui et al. (2023), Noy and Zhang (2023) for writing tasks, Peng et al. (2023) for IT developers, and Toner-Rodgers (2024) for scientists). Whether these results apply to other occupations is an open question.

to perform certain tasks and switch to other tasks instead. Our analysis can distinguish between task changes within and between occupations and track these changes over time. Moreover, workers might respond to the new technologies by switching employers, occupations, or industries, as not all jobs and sectors are equally exposed to AI or robots. Our paper provides the first evidence of how workers might use their outside opportunities to adjust to the emergence of AI. Finally, we also explore to what extent these adjustments affect workers' wages.

A key challenge for our analysis is how to measure the new technological opportunities of AI. We use a novel measure to characterize the evolution of AI and robots, which we developed by applying NLP on the universe of patents from the European Patent Office (EPO) (Gathmann and Grimm, 2024). We pool patents from all inventors filed at the EPO and match them to the industries most likely to *use* them, thereby reducing concerns about reverse causality. We show below that task shares cannot predict subsequent technology patents in using industries, and that results are robust to dropping patents filed by German inventors. Our measures then capture the evolving capabilities of AI and robots across detailed industries and within industries over time. Reassuringly, the patent-based robot measure is highly correlated with actual robot installations in manufacturing industries, which is commonly used in studies on robots (Acemoglu and Restrepo, 2020, Dauth et al., 2020, Graetz and Michaels, 2018). We further document that our patent-based AI measure shows a strong association with job ads requiring AI skills and firms mentioning AI on their website. A key advantage of our industry-level measures is that they enable us to analyze AI's impact on the task content of occupations, and the workers employed in those occupations, and trace their dynamics over time.

We start out investigating how AI changes job tasks, both within and across occupations and contrast the results with the better-known effects for robots. To do so, we combine our industry-level technology measures with individual survey data on the tasks workers perform on their jobs. These data have previously been used to study task human capital (Gathmann and Schönberg, 2010) and technology-related changes in job tasks (Spitz-Oener, 2006). Our empirical analysis relies on within-industry variation in AI and robot exposure over time between workers who have similar socio-demographic characteristics and are employed in the same occupation.

Our first novel result is that AI has decreased abstract tasks in jobs, in particular in the category of 'gathering information and investigating'. In contrast, AI has increased the need for 'high-level' routine tasks such as monitoring processes, which require the use of a computer or tablet. Most of the changes occur within detailed occupations, indicating that AI shifts the assignment of workers to tasks. The effects have become more pronounced as the capabilities of AI expanded over time. We further show that the impact of AI on job tasks differs sharply from that of robots. Robots have increased the demand for non-routine tasks and reduced the demand for routine tasks. The task changes we find using robot patents are very similar to previous studies using robot installations (e.g., Graetz and Michaels, 2018, Acemoglu and Restrepo, 2020, Dauth et al., 2021), providing further support for the validity of our patent-based measures. The task shifts we document challenge the view that AI might continue previous technological trends of automating mostly routine tasks.

Our second novel result is that the task changes associated with AI affect all workers but are not skill-neutral. Both low- and high-skilled workers see a decline in the analytical task of 'gathering information and investigating', and an increase in the routine task of monitoring processes. Yet, high-skilled workers also increase their activities in educating and training. Though both skill groups are affected by the automation of some abstract tasks, high-skilled workers can leverage their comparative advantage and expertise to switch to other abstract tasks like training and educating. The possibility to perform other tasks thus shields high-skilled workers partially from the effects of automation, while low-skilled workers see their abstract task share decline.

We then turn to administrative social security data to understand the consequences of the observed task changes for worker careers. In line with earlier studies, we document that AI has so far not destroyed many jobs in exposed industries. That does not mean that AI has not had an imprint on the labor market, however. We do see sizable adjustments to AI at the worker level. Our third novel result is that AI has resulted in worker reallocation across establishments. About half of the job mobility is within the same detailed industry, while the other half is into similar, but different industries that are less exposed to AI. As for the task changes, the reallocation of workers in response to AI differs sharply from the worker-level adjustments to robots. In line with prior evidence from Germany (Dauth et al., 2021), we find that robots increased employment stability at the initial establishment.

Our final novel result is that the reassignment of tasks across workers has reduced the wages of low-skilled workers in exposed industries –irrespective of whether they switch jobs or not. The modest decline in wages indicates that the loss from automation exceeds any productivity gains for low-skilled workers in Germany. In contrast, high-skilled workers, though also affected by automation, do not experience wage declines on average. Incumbent workers actually benefit from wage gains, possibly reflecting productivity gains and their comparative advantage in their job. Our results thus confirm task-based models that AI can indeed result in wage losses for some workers if

AI is mainly deployed for automation and workers cannot exploit some comparative advantage to compensate for the automated tasks easily.

The findings in this paper have a number of important policy implications for the transition into the age of AI. The fact that AI can substitute for non-routine tasks in all skill groups highlights that AI will affect many more workers, including those high up the skill distribution. A second implication is that workers are hit hardest if they cannot exploit some comparative advantage in other tasks to substitute for automated tasks. Promoting on-the-job training and upskilling to strengthen competencies in complementarity skills and workers' comparative advantages becomes then key to cushioning the potentially disruptive effects of AI in the labor market. Finally, our findings document that the adjustments to evolving AI have so far occurred primarily through worker reallocation. Policy-makers could then provide incentives for encouraging worker mobility or job search assistance to identify suitable job opportunities in other industries, for instance.

Our paper contributes to several strands of the literature. In addition to studies on the labor market effects of AI, our paper builds on the empirical task literature, which has documented sizable changes in job tasks both within and between occupations in response to supply side changes (Bittarello et al., 2018) or demand side changes (Consoli et al., 2023, Ross, 2017, Spitz-Oener, 2006). The literature linking technological change to job tasks has largely focused on changes between occupations (e.g., Autor et al., 2003, Gregory et al., 2022). We contribute to this literature by showing that most observed changes in tasks occur within occupations rather than between them. This result highlights that the labor market challenges of AI go well beyond job displacement and worker reallocation across jobs.

Our study also relates to the literature on automation technologies. One strand of this literature is concerned with the diffusion of robots in the economy (e.g., Graetz and Michaels, 2018, Acemoglu and Restrepo, 2020, Dauth et al., 2021, Koch et al., 2021, Humlum, 2019, Bonfiglioli et al., forthcoming). Studies of robots have mostly focused on employment and wage effects, in addition to adjustments at the worker and firm level. We contribute to this literature by analyzing how robots shift job tasks. Furthermore, by comparing the effects of robots and AI, we show that both technologies have very different, often opposing effects on jobs, worker careers, and wages. A second strand of the automation literature studies the reallocation effects of technology adoption at the firm level (Bessen et al., 2019, Genz et al., 2021). We contribute to this literature by zooming in on two specific technologies, AI and robots. Moreover, we focus on how incumbent workers respond to the diffusion of AI and the impact on their wages.

The rest of this paper is structured as follows. The next section outlines our approach to measuring advances in AI and robotics technologies using patent data. In sections 3 and 4, we explore how AI has shifted the task content of jobs and compare it to the impact of robots. In section 5, we analyze how workers adjust to the changes initiated by AI technologies and document wage and employment effects. Finally, section 6 discusses the implications of our findings and concludes.

2 Measuring Advances in AI and Robotics

2.1 Patent Data

A key challenge in assessing the impact of AI technologies on the content of jobs and the labor market more broadly is to find a suitable measure of who is exposed to AI. Our measures of technological progress in AI and, for comparison, robotics are based on patent data from the European Patent Office (EPO). Patents are proxies for technological advances which have been heavily used in the innovation literature. We use the universe of patents granted by the EPO between 1990 and 2018. These data include detailed bibliographical and technical information on all patents filed and granted. In total, we use around 7 million patent documents, containing the title of the invention, an abstract describing the invention as well as information on the inventor such as name, company, and location. Many patents are filed by non-European inventors who want to protect their innovations when selling on European markets. Importantly, each patent's technical content is classified in the Cooperative Patent Classification (CPC) and is assigned one or more codes by a specialized patent examiner.

2.2 Develop New AI and Robot Measures

We create a measure of advances in AI and robotics in three steps (see Gathmann and Grimm, 2024, for more details). The first step is to classify patents as AI or robotics patents. For robots, we identify them mostly by the CPC code B25J9 'Programme-controlled manipulators'. For AI, we use a combination of a search based on AI-specific CPC codes and a keyword-based classification that uses the patent's title and abstract as inputs. AI is frequently embedded in other inventions because algorithms and software may not be protected by patents on their own. Patent protection is granted, however, if the algorithms or software are part of the solution for a technical problem like image recognition, for example. To capture inventions that involve AI but are not classified by an

AI-specific CPC code, we use Natural Language Processing (NLP) to classify AI patents based on keyword matches. We prepare the text input using NLP techniques, such as stemming, the removal of stop words, and tokenization. We then use keyword matches to find AI-related inventions. This approach yields around 7,000 AI patent applications and grants. Appendix Figure A.1 shows the number of AI and robot patent grants per year during our sample period. The figure shows that AI-related patenting in Europe has started to grow in the 2000s, but has taken off after 2015. In contrast, patenting in robots has already been sizable in the late 1990s, but shows a substantial increase after 2005.

The second step is to identify the industries that make use of AI or robots patents in their production of goods or services. It is important to stress that we do *not* want to identify the producers of patents ('innovators'); instead, we care to identify the industries that potentially use the technological innovations protected by patents ('firms using innovations'). Industries that produce a patent need not be the same as the industries using a technological innovation. A patent on an AI technology might be filed by a company in the IT sector but is later used in the manufacturing of machinery or in agriculture, for instance. For the mapping from CPC codes to industries of use, we employ a probabilistic walkover developed by Lybbert and Zolas (2014) and updated by Goldschlag et al. (2019)[2]. The walkover allows us to go from CPC codes to detailed (3-digit) industry codes. More specifically, Lybbert and Zolas (2014) use the description of industries and the economic activities performed in them to run a keyword search on the universe of patents in the PATSTAT database. This approach identifies patents whose technological content is closely related to a given industry. Using the CPC codes of the matches obtained in this search, they calculate the probability that a patent belonging to a CPC code is linked to a specific industry. Based on the frequency of patent-industry matches, they calculate a probabilistic weight using Bayes' rule. They hereby take into account the total number of possible codes and the number of times a code is matched to an industry. This approach results in a list of patents with their CPC codes linked to industries that produce goods and services with the knowledge embedded in the patent.

The final step is to construct a summary measure of the advances in AI. We consider patents as the cumulative stock of knowledge on certain technologies that is available to firms for implementation in a given year. We therefore construct the following measures:

$$AI_{jt} = \sum_{s=1990}^{t} Log(1 + AIPat_{is}), \tag{1}$$

[2]See also Goldschlag et al. (2016) for applications of this probabilistic walkover from patents to industries.

and

$$Robots_{jt} = \sum_{s=1990}^{t} Log(1 + RobPat_{is}) \quad (2)$$

where j denotes the industry, s the year of the patent grant and t denotes the period from 1990 to year t. We follow the literature and give each patent the same weight (e.g., Mann and Püttmann, 2023).[3] For both AI and robots, the measure varies by 3-digit industry and over time. Appendix Table A.1 shows that AI exposure is highest in the industries 'Manufacture of computers and peripheral equipment', 'Manufacture of consumer electronics', and 'Manufacture of communication equipment'. While AI exposure is highest in manufacturing during our sample period, there are also exposed industries in the service sector such as 'Motion picture, video and television programme activities', 'Sound recording and music publishing activities', or 'Medical and dental practice activities'. In sharp contrast, robot exposure is highest in manufacturing and in particular, industries 'Manufacture of general-purpose machinery', 'Manufacture of special-purpose machinery', and 'Manufacture of other fabricated metal products, metalworking activities'. The two technologies are also not independent of each other; on the contrary, our measures of AI and robot exposure show a sizable positive correlation at the industry level (correlation coefficient 0.53).

2.3 Validation of Measures

It is important to verify that our measures of AI and robot exposure also capture the actual implementation of an AI or robot technology in exposed industries. To validate our robot measure, we exploit the widely-used data on robot installations from the International Federation of Robotics (IFR) (International Federation of Robotics, 2021). Unfortunately, the IFR data are available for a much smaller set of industries than our patent-based measures of robots. After adjusting our measure to the industry classification, Panel A of Appendix Figure A.2 shows a strong positive link between our exposure measure and the actual installation of robots, suggesting that our measure of robot exposure is a good predictor for actual robot installations.

Given the recent nature of AI technologies, it is much harder to find good proxies for the implementation of AI. Our first proxy follows recent papers on AI using the number of online job ads in Europe mentioning at least one AI skill. The second proxy uses information from firms' webpages to classify firms as AI users based on data from Istar.ai.[4] Panels B and C of Appendix

[3] Weighting by forward patent citations to indicate the importance of a patent is not feasible given the recent nature of patent activity we analyze.

[4] Firms are classified as AI users if they mention investments in AI like data analytics, but also if they have a chatbot on their webpage, for example.

Figure A.2 show that our AI exposure measures are strongly positively correlated with both proxies for AI use at the industry level. We next discuss the data and strategy to analyze the impact of AI and robots on job tasks.

3 AI and Job Tasks: Data and Empirical Strategy

3.1 Data on Tasks Performed on the Job

To analyze how AI affects the tasks workers perform in their jobs, we make use of the BIBB/BAuA surveys (Hall and Tiemann, 2009, Hall et al., 2014, 2020). The data have previously been used to analyze changes in job tasks over time (Spitz-Oener, 2006) and the impact of task distance on worker mobility and earnings growth (Gathmann and Schönberg, 2010). The survey is a repeated cross-section of employees that has been conducted roughly every six years since 1979. Each survey consists of a representative sample of individuals ages 15 and older who work at least 10 hours per week at the time of the interview.

We focus on the three most recent waves of 2006, 2012, and 2018, for which the task-related questions are identical in each wave, allowing us to study changes over time in tasks performed on the job. We restrict the sample to individuals between the ages of 18 and 65, working full-time (at least 35 hours per week) in dependent employment. The survey contains the socio-economic background of the individual including educational background and age, but also the detailed occupation and industry. Our analysis distinguishes between high-skilled workers with a university degree and low-skilled workers without a university degree.

Most importantly, the survey elicits whether an individual performs any of seventeen different tasks. We analyze the detailed tasks and aggregate them into three broad categories: routine tasks, non-routine abstract tasks, and non-routine manual tasks. The individual tasks and their classification into the three groups are as follows:

Routine tasks: Monitoring or operating machines or technical processes; manufacturing or producing of goods and products; transporting, storing or shipping; measuring or quality checks.

Non-routine abstract tasks: Developing, researching or constructing; gathering information, investigating or documenting; working with computer or tablet; organizing, planning or preparing work processes (of others); Buying, procuring or selling; teaching, training or educating; consulting or informing; promoting, marketing, advertising or PR.

Non-routine manual tasks: Repairing; accommodating, hosting or preparing food; caring or healing; cleaning, waste disposal or recycling; protecting, securing, guarding or regulating traffic.

For each task, survey participants are asked whether they perform the respective task 'frequently', 'occasionally', or 'never' in their job. Based on the answers, we compute task shares for our three broad task categories. For each task category c, we compute the number of tasks performed frequently or occasionally, which fall into category c, divided by the total number of all tasks performed (frequently or occasionally) by worker i:

$$TaskShare_{it}^{c} = \frac{\sum_{r \in c} Task_{irt}}{\sum_{r} Task_{irt}} * 100 \tag{3}$$

where t denotes the survey wave and r is a specific task. $Task_{irt}$ is equal to one if the individual performs task r frequently or occasionally in year t; and zero otherwise. The task share takes on values between 0% and 100% and can be interpreted as the relative importance of category c in worker i's job. For example, if worker i performs a total of four tasks and two of them fall into the routine category, then the routine task share equals 50%. Our findings do not depend on this particular definition of task share as we discuss below. In our empirical analysis, we will analyze both the aggregate task shares and the prevalence of each task individually to track which tasks change in a job. It is important to stress that the survey does not add new tasks during our sample period. Therefore, changes in the prevalence of performing a task are likely to include automation of some aspects, productivity gains in others and the emergence of new aspects within the same task.

Appendix Table A.2 shows descriptive statistics for each wave separately (2006, 2012, and 2018). Panel A shows that the routine task share decreased by 0.8 percentage points and the manual task share decreased by 1.3 percentage points between 2006 and 2018. Conversely, the abstract task share increased by roughly 2 percentage points over the same period. Panel B tracks the share of workers who perform one of the 17 tasks in the respective year. The decline in the routine tasks between 2006 and 2018 is driven by the categories 'Monitoring/operating machines/technical processes', 'manufacturing/producing of goods/products', and 'transporting, storing, shipping'. In contrast, the increase in abstract tasks comes from the categories 'Developing, researching, constructing', 'Gathering information, investigating, documenting', 'Organizing/planning/preparing of work processes (of others)', and 'Working with computers/tablets'.[5]

[5]Appendix Tables A.3 and A.4 show for each individual task the top three occupations which exhibit the largest share of workers performing the respective task.

The task content of jobs differs substantially between skill groups. College-educated workers mostly perform abstract tasks (72.8%), while the routine task share is only 15.8% and manual tasks make up the remaining 11.4%. In contrast, workers without a university degree have higher routine (26.3%) and manual (21.6%) task shares, but a lower abstract task share (52.1%). These differences will be important when we analyze who is affected most by the observed task changes due to AI and robots.

3.2 Empirical Strategy

To investigate task changes on the job and the role played by technological advances, we merge our AI and robot exposure measures to the individual worker samples by two-digit industry and period.[6] We then estimate variants of the following model:

$$Y_{ijot} = \beta_1 AI_{jt} + \beta_2 Robots_{jt} + X'_{it}\gamma + \mu_j + \theta_o + \tau_t + \epsilon_{ijot} \tag{4}$$

Y_{ijot} denotes the outcome of worker i who is employed in 2-digit industry j and 2-digit occupation o in survey year t (2006, 2012, or 2018). We start out with analyzing the three broad task shares (routine, abstract, or manual), as defined in equation (3). We then proceed with an analysis of the 17 detailed tasks as outcome measures to understand how job contents have been changing. An additional advantage of studying the detailed tasks performed by workers is that they are measured as indicators, avoiding the adding-up constraint in the aggregate task shares.

The main explanatory variables of interest are AI_{jt} and $Robots_{jt}$, the cumulative number of AI or robot patents between 1990 and the survey wave (t) in using industry j (as defined in equation 1). Allowing for a time lag in the diffusion of technologies has little effect on our results as we show below. We include a number of demographic characteristics as control variables X_{it}: the education level, age groups (18-25, 26-35, 46-45, 46-55, 56-65), gender, and German nationality. We further include fixed effects for 2-digit occupations (θ_o) and 2-digit industries (μ_j) as well as state and wave fixed effects t_t. All specifications use sample weights and cluster standard errors at the industry-year level. The parameters of interest, β_1 and β_2, are then identified from within-industry variation in AI and robot exposure over time between workers with similar socio-demographic characteristics and who are employed in the same 2-digit occupation.

[6] More specifically, we aggregate up our patent measures to the level of 2-digit ISIC rev.3 industies. This corresponds to the 2-digit industry classification in the BIBB/BAua data (WZ03). In the second part of the analysis, using administrative data, we exploit our patent measures at the 3-digit industry level.

3.3 Balancing Test: Do Tasks Predict Future Exposure?

A potential concern with our empirical strategy in equation (4) is reverse causality. Rather than technological change shifting job tasks, job tasks might affect future technological progress. Growing specialization or outsourcing of firms in response to globalization or other produce demand shocks might shift the tasks performed in certain jobs, which in turn encourages firms to invest in automation or AI adoption, for example. In such a case, the shift in tasks would be the cause rather than the consequence of exposure to AI.

To address these concerns, we run a balancing test to determine whether initial task shares (in 2006) help to predict future exposure to AI or robotics technologies. In Table 1, we regress changes in our patent measures between 2006 and 2018 on task shares in 2006 at the industry level. In Panel A, we perform this analysis at the 2-digit level (56 industries) using our task data. In Panel B, we perform the analysis at the 3-digit level (233 industries). Here, we make use of the occupational employment structure within industries from administrative social security records (the data used in Section 5 below). We first merge the task shares in 2006 to the administrative data at the 2-digit occupation level; and then regress the task shares at the 3-digit industry level in 2006 on AI and robot exposure at the 3-digit level.

Table 1 shows that conditional on broad sector dummies, initial task shares in 2006 do not predict future patent exposure more than a decade later. The first specification (in columns (1) and (3)) looks at the raw correlation at the industry level, while the second specification (in columns (2) and (4)) controls for differences in job tasks between broad sectors (agriculture, manufacturing, and services).

The raw correlations show a marginal positive correlation between AI technologies and routine task shares at the 2-digit industry level (see column (1) of Panel A) and a positive correlation between robots and routine task shares at the more detailed 3-digit industry level. Yet, once we control for the substantial differences in tasks across broad sectors, the coefficients get very small, flip signs, and turn statistically insignificant. Moreover, the coefficients are economically very small both in absolute value (recall that the task shares range from 0 to 100) and also relative to the large coefficient for manufacturing. The main message to take away from Table 1 is that reverse causality does not seem to be a major concern for our analysis.

Table 1: Balancing test

Panel A:	Δ AI Exposure (2006-18)		Δ Robot Exposure (2006-18)	
2-digit industries (BIBB)	(1)	(2)	(3)	(4)
Routine task share 2006 (%)	0.75**	-0.07	1.21	-0.76
	(0.35)	(0.46)	(0.73)	(0.54)
Abstract task share 2006 (%)	0.29	0.02	0.17	-0.47
	(0.23)	(0.26)	(0.42)	(0.29)
Manufacturing sector		9.97***		23.81***
		(3.43)		(6.57)
Primary sector		-1.40		-3.25
		(1.45)		(2.06)
Std. Dev. of Y variable	7.27	7.27	13.03	13.03
R^2	0.17	0.34	0.26	0.56
Observations	56	56	56	56

Panel B:	Δ AI Exposure (2006-18)		Δ Robot Exposure (2006-18)	
3-digit industries (SIAB)	(1)	(2)	(3)	(4)
Routine task share 2006 (%)	0.21	-0.21	0.85***	-0.21
	(0.18)	(0.18)	(0.38)	(0.26)
Abstract task share 2006 (%)	0.05	-0.07	0.20	-0.12
	(0.10)	(0.10)	(0.18)	(0.14)
Manufacturing sector		5.24***		13.32***
		(1.13)		(2.99)
Primary sector		0.01		-0.66
		(0.40)		(0.57)
Std. Dev. of Y variable	3.87	3.87	8.91	8.91
R^2	0.04	0.27	0.14	0.42
Observations	233	233	233	233

Notes: The table reports industry-level regressions of the change in AI exposure (columns (1) and (2)) and the change in robot exposure (columns (3) and (4)) between 2006 and 2018 on task shares in 2006 and broad sector dummies (agriculture, manufacturing and services). Regressions are weighted by the number of observations in the respective industry. In Panel A, task shares are computed at the 2-digit industry level from the BIBB survey. In Panel B, task shares are computed at the 3-digit industry-level from the administrative social security data (SIAB), using occupational task shares from the BIBB data. Robust standard errors are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

4 The Impact of AI on Tasks Performed on the Job

4.1 Industry-level Correlations

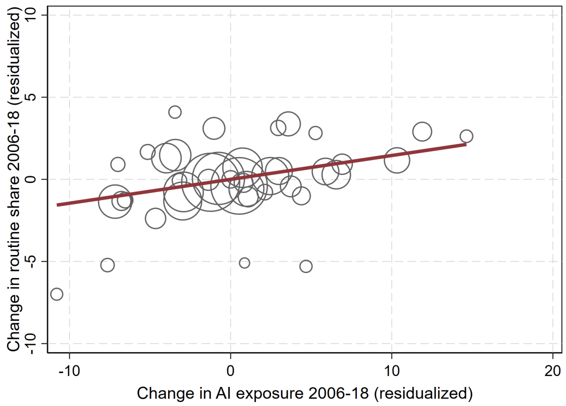
We start with simple descriptive evidence relating changes in job tasks to changes in our patent-based measures of AI and robot exposure. Figure 1 plots the change in the routine, abstract, and manual task shares between 2006 and 2018 against the changes in the AI and robot exposure measures between 2006 and 2018. We first residualize task shares and changes in technology exposures from demographics and broad sectors.[7] The circle reflects the size of the industry and the regression lines are based on a regression weighted by size.

Surprisingly, Panel A shows a positive correlation between AI technologies and the relative importance of routine tasks. In sharp contrast, robot exposure (shown in Panel B of Figure 1) shows a strong negative correlation with the routine task share, confirming prior evidence that robots automate routine tasks and jobs (e.g., Acemoglu and Restrepo, 2020, Dauth et al., 2021, Webb, 2020). It is reassuring that our robot measure shows very similar results to studies using actual robot installations based on a smaller set of industries, increasing our confidence that our measures indeed capture technological advances in the using industries.

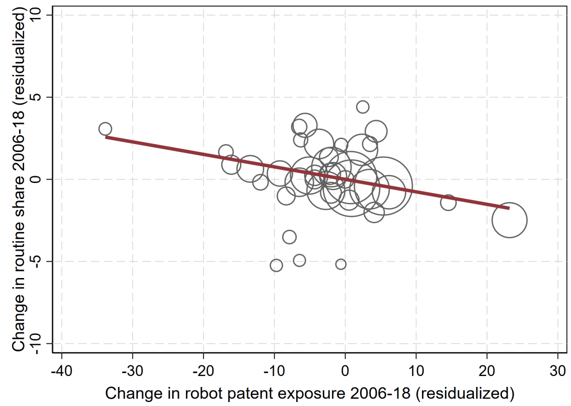
Panel C and D in Figure 1 turn to the relationship between new technologies and abstract tasks. AI technologies are associated with a decline in abstract tasks, while robots are slightly positive correlated with abstract tasks. Finally, Panels E and F show that AI and robot technologies have little association with changes in the manual task share. Overall, these industry-level correlations provide a first hint that AI affects the task content of jobs in fundamentally different ways than robots.

[7] Demographic controls include education groups, age groups, gender, and German nationality in the industry. Sector controls are manufacturing, services, and the primary sector.

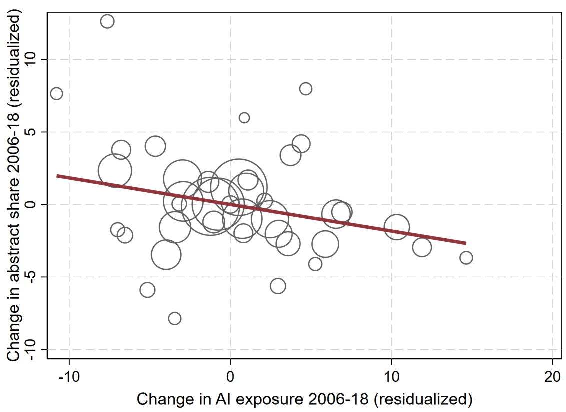
Figure 1: AI, Robots, and Task Changes at the Industry Level



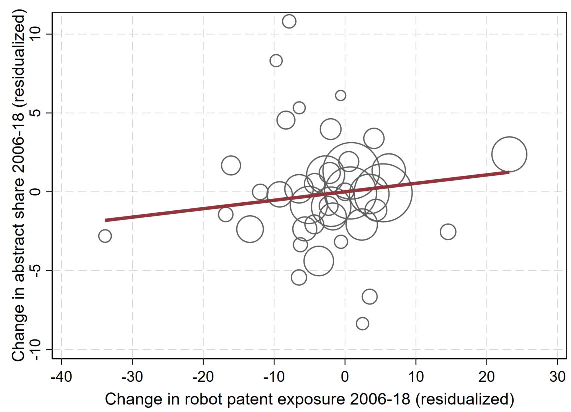
(a) AI and Routine Tasks



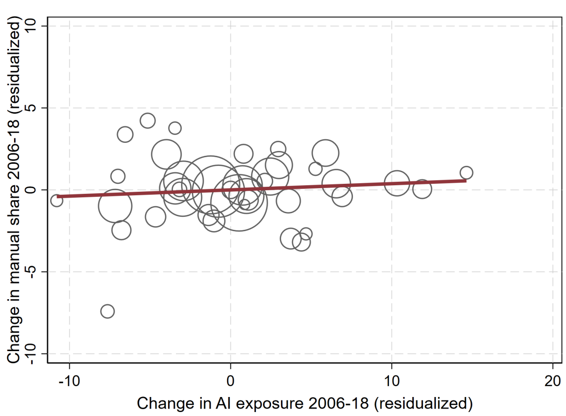
(b) Robots and Routine Tasks



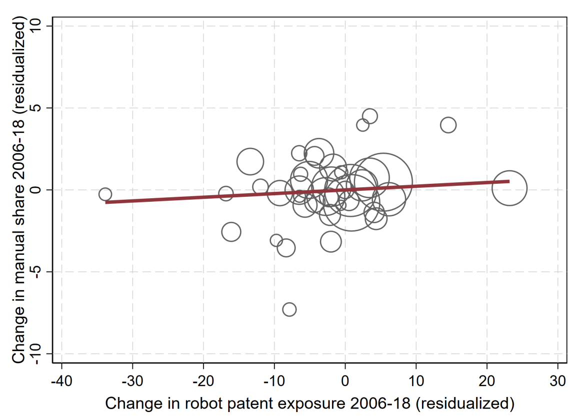
(c) AI and Abstract Tasks



(d) Robots and Abstract Tasks



(e) AI and Manual Tasks



(f) Robots and Manual Tasks

Notes: The figure shows the relationship between changes in task shares and changes in AI (left-hand side) or robot exposure (right-hand side) between 2006 and 2018 at the industry level. All variables are residuals after adjusting for demographic characteristics and broad sectors. Demographic controls include education groups, age groups, gender, and workers with German nationality, measured in 2006. We also include dummies for three broad sectors (agriculture, manufacturing and services). The size of the circle denotes the number of employees in the industry in 2006. The figure is restricted to industries with at least thirty employees in our sample in 2006.

4.2 AI and Worker-Level Tasks

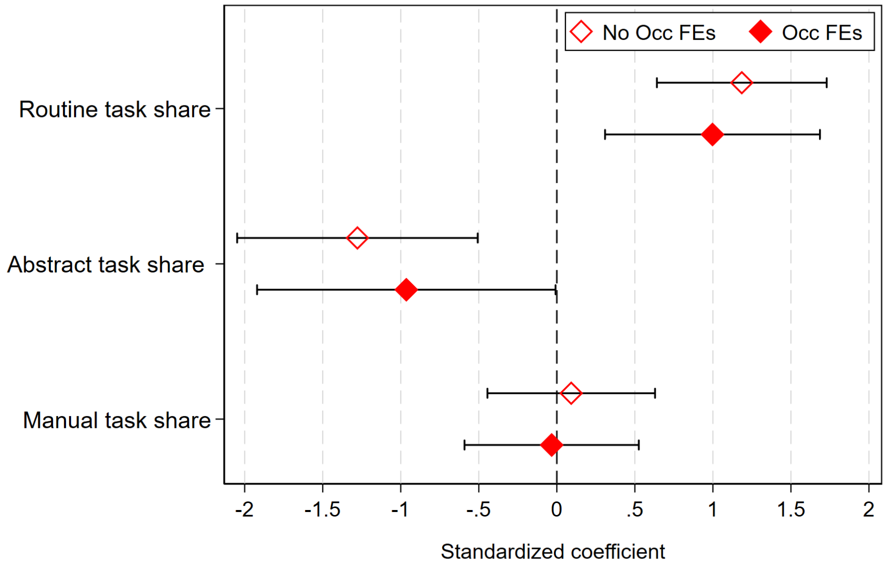
We now turn to the worker level and estimate how exposure to AI and robots affects individual task shares by estimating equation (4). We control for 2-digit industry and year fixed effects, socio-demographics, and federal state dummies. Figure 2 shows the results for overall task changes and zooming in on task changes within occupations. The first specification (hollow diamonds) shows overall task changes, which combines changes in the composition of occupations *and* task changes occurring within occupations. The second specification zooms in on task changes within detailed occupations by including (2-digit) occupation fixed effects. To facilitate the interpretation, the figure shows the estimated impact of a one standard deviation increase in the AI and robot exposure measure on the three broad task shares.

Panel (a) of Figure 2 confirms the stunning pattern that AI *increases* the routine task share of workers and *decreases* their abstract task share, with no effect on their manual task share. Interestingly, a comparison of the two specifications suggests that most of the overall task changes occur *within* occupations, indicating that AI shifts the assignment of workers to tasks. Our finding that the adjustments mostly occur within detailed occupations is important given that most of the literature on technology and tasks has focused on changes between occupations. For robots, we find the opposite pattern. In line with the idea that robots automated routine tasks (e.g., Acemoglu and Restrepo, 2020, Dauth et al., 2021, Webb, 2020), we show that robot exposure is associated with a decline in the routine task share with few changes in the abstract and manual task shares.

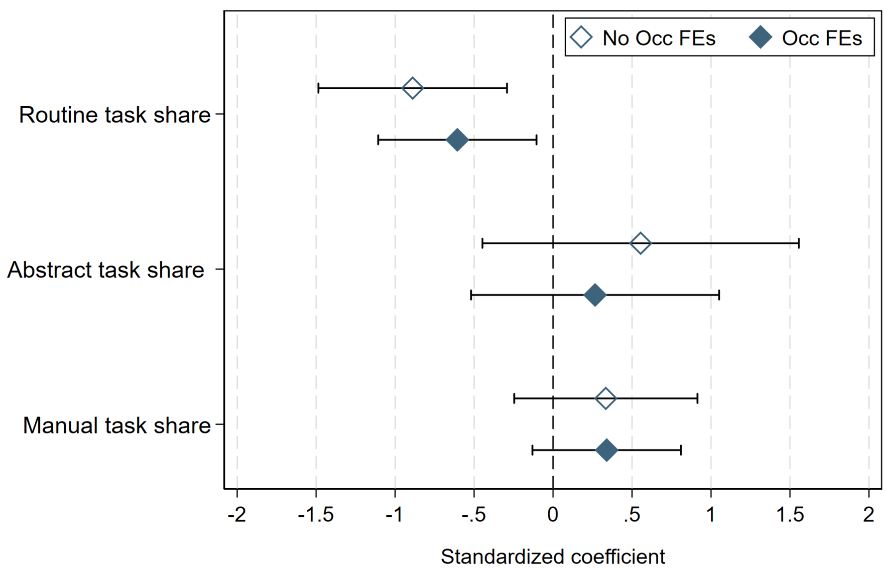
How large are the estimated effects of AI and robots on tasks? An increase in robot exposure (by one standard deviation) reduces the routine task share by 0.9 percentage points in total and by 0.6 percentage points within occupations. While these effects are small compared to the cross-section variation of task shares, they account for virtually all of the decline in the routine task share between 2006 and 2018 (see Appendix Table A.2). Turning to AI, we find that an increase in AI exposure (again by one standard deviation) increased the routine share by roughly 1 percentage point and decreased the abstract task share by about 1 percentage point. The findings indicate that the decline in routine task shares and the growth in abstract task shares would have been even faster in the absence of AI.[8]

[8] Appendix Table A.5 shows the actual point estimates for alternative specifications.

Figure 2: AI, Robots and Job Tasks at the Worker Level



(a) AI



(b) Robots

Notes: The figure shows point estimates and 95%-confidence intervals of a one standard deviation increase in exposure to AI (Panel a) or robots (Panel b), respectively. The estimates are obtained from a regression of each task share on AI and robot exposure controlling for 2-digit industry fixed effects and year fixed effects. In addition, we include as demographic controls education, gender, age groups (18-25, 26-35, 36-45, 46-55, 56-65), German nationality and federal state dummies. Number of observations: 37,415. Standard errors are clustered at the industry-year level.

If our results indeed reflect the diffusion of AI in the labor market, we would expect the effects to become more pronounced over time as the capabilities of AI have vastly expanded since 2006. Appendix Table A.6 shows in columns (2) to (4) separate estimates for each survey wave. The most important finding is that the impact of AI on routine and abstract tasks is small and statistically insignificant in 2006 but the effect more than doubles and becomes statistically significant by 2018. The temporal pattern of the estimates provides additional support for our empirical strategy and findings. In Appendix Figure A.3, we further demonstrate that our results are robust across a variety of alternative specifications. First, we experiment with alternative ways of creating our AI and robot exposure measures. The Figure shows that our results are very similar when we use the absolute number of patents instead of the log transformation, when we drop German patents from our measure (due to potential reverse causality), and when we lag our exposure measures by three years. In addition, the results also hold when we construct the task shares in different ways. Remember that, in our baseline specification, we assign a value of 1 if the respective task is performed ’frequently’ or ’occasionally’ and 0 otherwise. Figure A.3 shows that, when we assign a value of 1 if the task is performed ’frequently’ and 0 otherwise, the point estimates become even larger. Analogously, the point estimates become slightly larger when we account for intensive margin changes in more detail by assigning a value of 2 for ’frequent’ task use, 1 for ’occasional’ task use, and 0 otherwise.

The surprising finding that AI technologies appear to lower the abstract and increase the routine task share of jobs raises the question of which specific job tasks change with AI. To investigate this, we use information on the seventeen detailed tasks available in the survey. We then re-estimate equation (4) where we now have the probability of performing a detailed task as the dependent variable. The results are conditional on occupation fixed effects and thus focus on changes within 2-digit occupations.

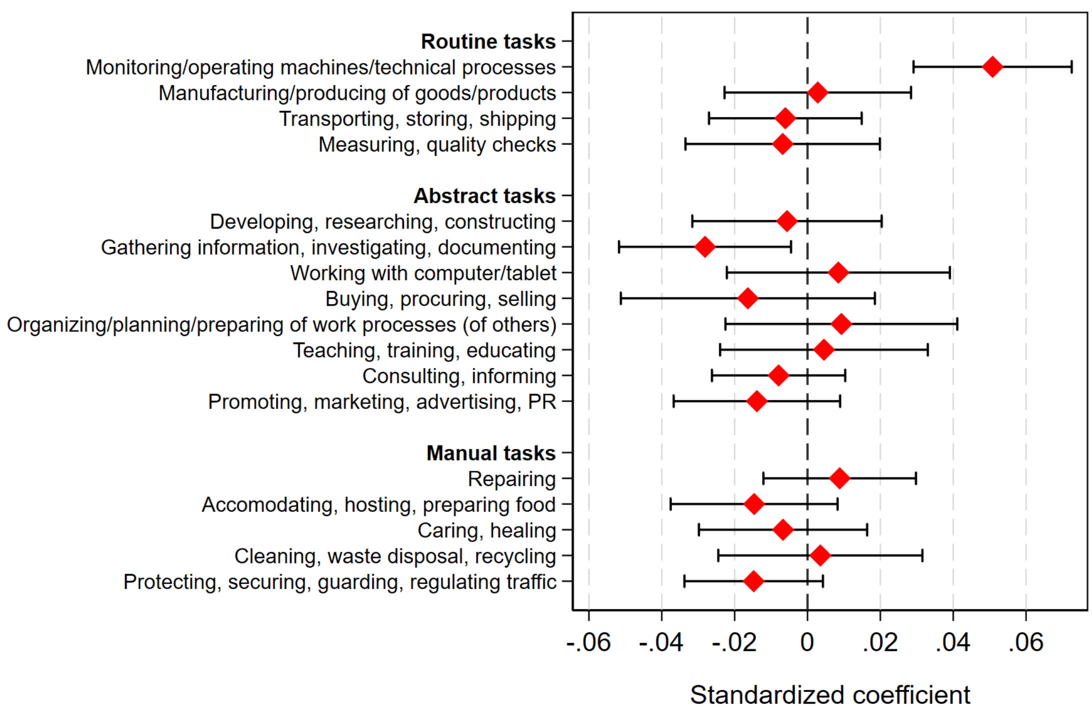
Figure 3 shows that the decline in abstract tasks is largely accounted for by a decline in the task of ‘gathering information, investigating, and documenting’. AI-assisted tools like data analytics, screening tools, or predictive maintenance technologies provide different layers of information, therefore reducing the need to collect and gather information manually.[9] The decline in the need to collect information indicates that AI can partially automate such tasks – even prior to generative AI. The effect is sizable: an increase in AI exposure (by one standard deviation) reduces the probability

[9]One example would be a malfunctioning machine where AI can diagnose the problem, whereas before, the responsible person had to call the service provider or study a handbook to fix the machine.

of performing this task by around 3 percentage points. The point estimates for other abstract tasks like 'Buying, procuring, selling', and 'Promoting, marketing, advertising, PR' are negative, but not statistically significant. Importantly, however, there are virtually no changes in the probability of working with a computer or tablet and in the probability of doing high-end abstract tasks like 'Developing, researching, constructing'.

Figure 3 further shows that the AI-induced rise in the routine task share exclusively comes from an increased likelihood of 'monitoring or operating machines and technical processes'. This effect might reflect the fact that AI-assisted tools help workers monitor other machines or technical processes, but also require the worker to oversee the output of the technical processes of AI themselves. We now investigate this link between AI and routine tasks in more detail.[10]

Figure 3: AI and Detailed Job Tasks



Notes: The figure shows the effect of AI exposure (by one standard deviation) and the 95% confidence intervals on the probability to perform a single task. The dependent variable is a dummy variable equal to one if a worker performs a task on the job. Regressions control for 2-digit industry, 2-digit occupation and year fixed effects as well as demographic characteristics (education, gender, age groups (18-25, 26-35, 36-45, 46-55, 56-65), German nationality and federal state dummies. Regressions employ sample weights. Standard errors are clustered at industry-year level.

[10] Appendix Figure A.7 shows the corresponding task-level results for robots.

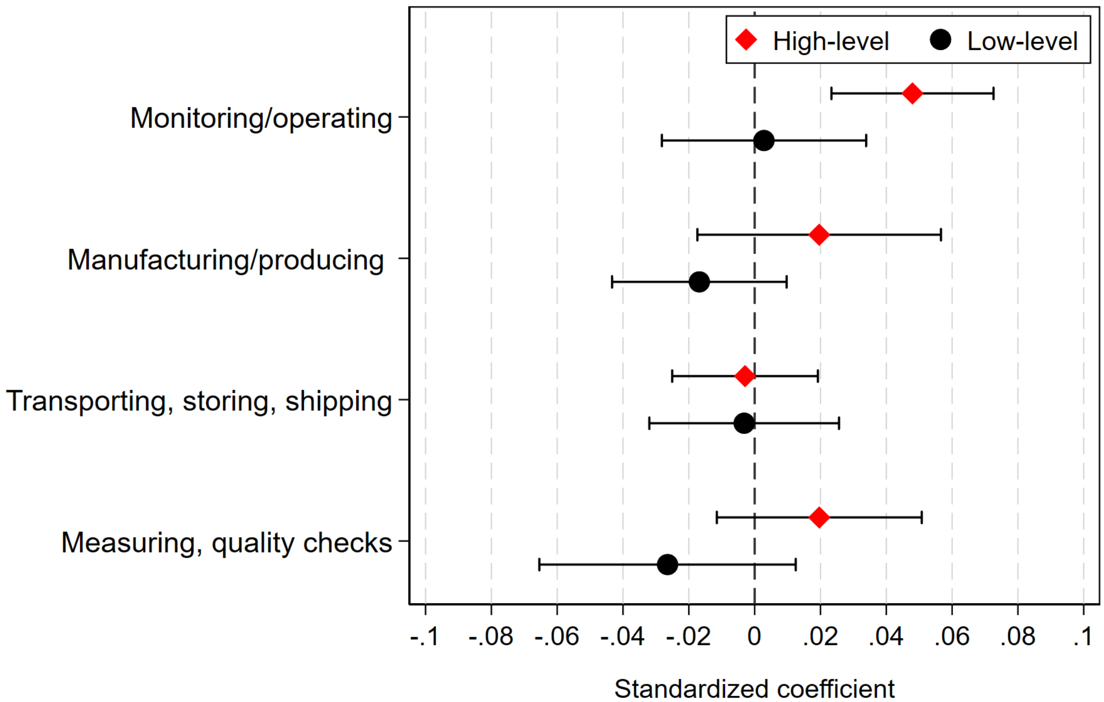
4.3 High-level Versus Low-level Routine Tasks

The result that industries exposed to AI saw an increase in the relative importance of routine tasks is novel and might seem surprising. The traditional view of routine tasks is that they can be easily codified into rules and eventually taken over by a machine. One example would be a repetitive task that a worker used to perform in an assembly line. We do not think that workers now switch (back) to tasks that are easily codified in response to AI. Instead, we think of the corresponding shift in task as a switch towards what we call 'high-level' routine tasks. High-level routine tasks are those that require humans to monitor and evaluate the process and results of algorithms, including the machines that algorithms might monitor and diagnose (see Figure 3).

To shed more light on the nature of routine tasks that complement AI, we define routine tasks as 'high-level' if a worker also reports working with a computer or laptop. In contrast, we define a routine task as 'low-level' if a worker reports not working with a computer or tablet. Appendix Table A.7 shows that high-level routine tasks are most prevalent among aircraft pilots, laboratory occupations in medicine, and occupations in physics. Individuals in these occupations are working in an environment with advanced technologies and are frequently required to analyze and interpret the output of technical processes or algorithms. In sharp contrast, the low-level version is most prevalent among occupations in gardening, occupations in building construction, and occupations in civil engineering.

We then re-estimate equation (4) where the dependent variable is now whether a worker performs a specific routine task at the high-level or the low-level. Otherwise, the specification is the same as before and includes all controls. The results in Figure 4 clearly show that the rise in routine tasks is concentrated among 'high-level' routine tasks, in particular in the task 'monitoring or operating machines and technical processes'. We see few changes in 'low-level' routine tasks, in turn. The findings that AI requires more 'high-level' routine tasks is not specific to the particular split into high- or low-level tasks. To demonstrate that, we use the following question: 'How often is the execution of your work prescribed down to the last detail?' We consider a given routine task as 'low-level' if the worker answers this question with 'often'. In contrast, we consider a given routine task as 'high-level' if the worker answers this question with either 'occasionally', 'seldom', or 'never'. Appendix Figure A.4 shows a very similar increase in 'high-level' routine tasks using this alternative definition of task complexity compared to the baseline. Together, they clearly show that AI raises the need for complex tasks that belong to the broad category of routine tasks.

Figure 4: AI and Low- versus High-Level Routine Tasks



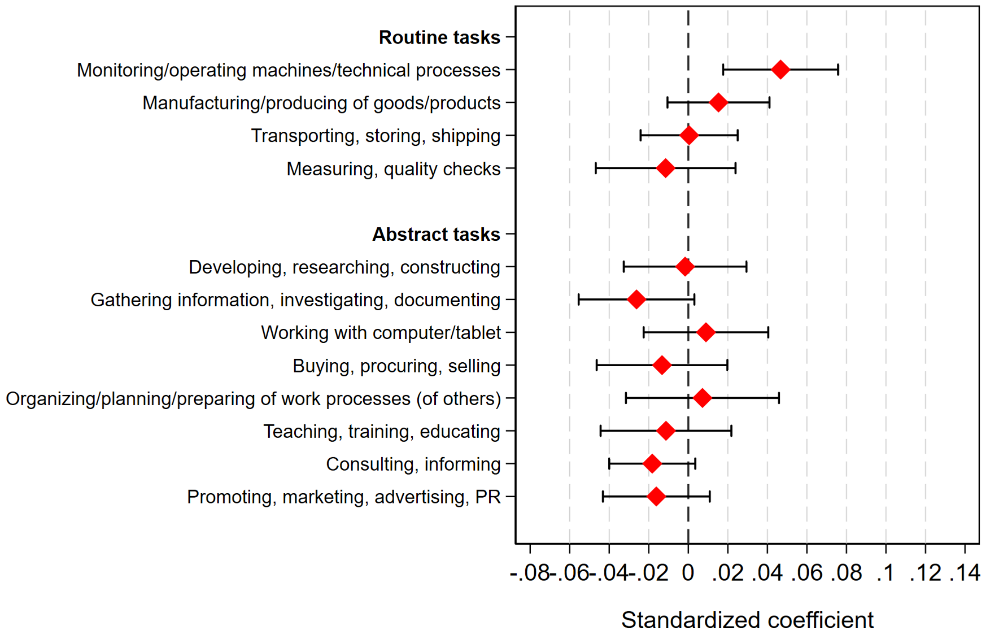
Notes: The figure shows the impact of AI exposure (by one standard deviation) on the probability of performing a specific routine task. We define a routine task as 'high-level' if a worker also reports working with a computer or laptop. In contrast, we define a routine task as 'low-level' if a worker reports not working with a computer or tablet. The estimation is based on equation (4) including all controls.

4.4 AI and Job Tasks by Worker Skill

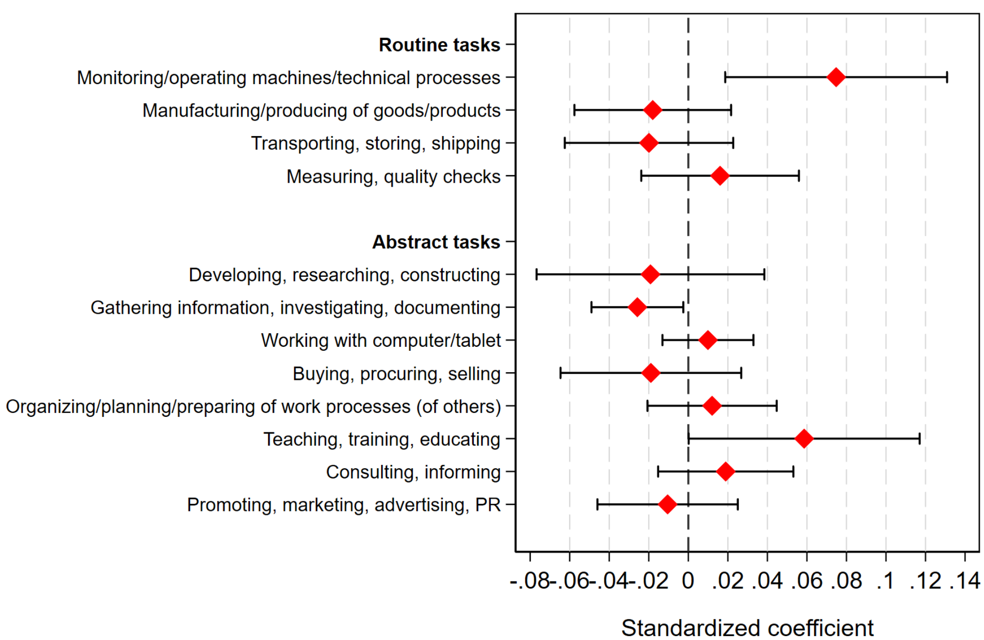
The finding that AI increases 'high-level' routine tasks might indicate that some workers are more affected than others. We focus here on differences between high-skilled and low-skilled workers. Our dependent variables are again the detailed routine and abstract tasks. The specification is the same as before.

Figure 5 shows several novel patterns. The first noteworthy pattern is that the AI-induced decline in performing abstract tasks is stronger among the low-skilled. More specifically, for low-skilled workers, six out of eight abstract tasks exhibit a negative point estimate though several are marginally insignificant. A second important result is that high-skilled workers in AI-exposed industries experience a large *increase* in the probability of 'teaching, training, and educating' as well as an increase in 'consulting, informing'. These positive effects fully offset the decline in other abstract tasks, such that high-skilled workers do not experience a decline in their abstract tasks overall. The point estimate for 'teaching, training, and educating' suggests that increasing AI exposure (by one standard deviation) raises the probability by a sizable 6 percentage points, which is larger than the raw change in the probability of performing the task between 2006 and 2018 (see Appendix Table A.2). The rise in teaching and training activities of high-skilled workers suggests positive complementarities between the diffusion of AI technologies, the need for learning-by-doing, and the expertise and comparative advantage of high-skilled workers.

Figure 5: AI and Detailed Job Tasks by Worker Skill



(a) Low skilled



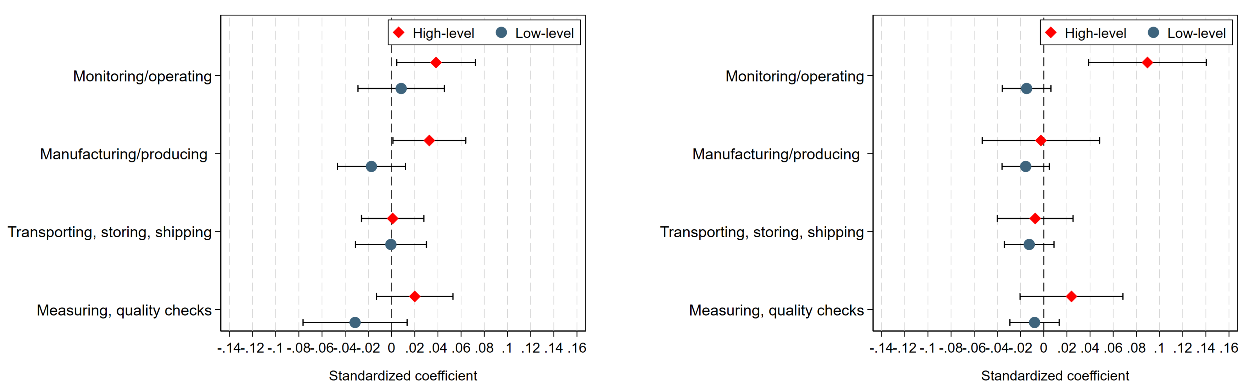
(b) High skilled

Notes: The figure shows the effect of AI exposure (by one standard deviation) and the 95% confidence intervals on the probability to perform a single task, separately for low-skilled (Panel A) and high-skilled workers (Panel B).

The final noteworthy pattern we observe in Figure 5 is that the AI-induced shift towards routine tasks, in particular towards 'monitoring or operating machines and technical processes', is strongest for high-skilled workers. We might expect this increase to be concentrated in the 'high-level' tasks discussed before; some of these might be even completely new monitoring tasks. To investigate this, we re-estimate our baseline specification in equation (4), focusing on 'high-level' routine tasks separately for high- and low-skilled workers. Figure 6 shows that low-skilled workers (Panel A) experience an increase 'high-level' routine task of 'monitoring/operating' and, to a lesser extent, 'manufacturing/producing' and 'measuring, quality checks'. For high-skilled workers, in contrast, Panel B shows a much larger increase in the 'high-level' routine task of monitoring machines and technical processes as well as a larger increase in 'measuring, quality checks' compared to low-skilled workers.

Overall then, our findings show that task automation affects all workers, even those with a college education. Yet, two countervailing forces benefit high-skilled workers: the first one is that they have the expertise and comparative advantage to switch to other tasks in response to AI. Moreover, they also benefit by seeing the demand for high-level routine tasks expand, which might be complementary to AI or could be entirely new specific tasks within the broader task captured in the survey.

Figure 6: AI and Routine Tasks for Low- and High-skilled Workers



(a) Low skilled

(b) High skilled

Notes: The figure shows the effect of AI exposure (by one standard deviation) and the 95% confidence intervals on the probability to perform a single task, separately for low-skilled (Panel A) and high-skilled workers (Panel B). We define a routine task as 'high-level' if a worker also reports working with a computer or laptop. In contrast, we define a routine task as 'low-level' if a worker reports not working with a computer or tablet.

5 AI and Labor Market Outcomes

Our findings thus far show that AI has begun to change the task content of jobs. The impact has mainly occurred within detailed occupations. Yet, how do these observed shifts in job tasks impact overall employment, worker mobility, and earnings of workers exposed to AI? One channel would work through automation: if, as the evidence in the last section indicates, AI automates some abstract tasks, and if there are no strong productivity gains working in the opposite direction, we might observe a decline in employment in exposed industries. The observed change in the task content of jobs could also reflect a reshuffling of workers, where workers remain in their occupation but leave exposed firms and industries to seek opportunities elsewhere. Whether and which workers see their earnings decline or increase because of AI will then depend on the relative size of the automation and productivity effects, as well as the outside options of workers in exposed industries. We now turn to administrative data on worker careers and earnings to investigate these important questions.

5.1 Administrative Labor Market Data

To study worker adjustments to AI, we use the 'Sample of Integrated Labour Market Biographies' (SIAB), a 2% random sample of the administrative social security records. The data cover about 80% of the German workforce, excluding self-employed, civil servants, and military personnel. We observe each individual's exact employment status, i.e., whether the person is employed, registered as unemployed, or non-employed; the data further records the daily wage. The detailed information enables us to analyze the employment and wage effects of AI and robot exposure. Moreover, we observe the occupation, firm, and industry of the worker, which we use to study worker reallocation in response to AI exposure. We further have detailed information on socio-demographic control variables such as education, age, gender, nationality, and plant location.

To match the data to our analysis of task changes, we aggregate the social security data at the worker level into three periods: 2004-2009, 2010-2015, and 2016-2021. The periods cover several years before and after the survey waves (in 2006, 2012, and 2018). Given the large sample in the social security data, we can merge our exposure measures to AI and robotics technologies at the even more detailed 3-digit industry level and period.

5.2 Estimation Approach

Our analysis of the impact of AI and robot exposure estimates variants of the following model:

$$Y_{ijot} = \beta^{AI} AI_{jt} + \beta^{Rob} Rob_{jt} + \theta_o + \delta_t + \mu_j + \gamma X_{it} + \epsilon_{ijot} \tag{5}$$

where Y_{ijot} is the labor market outcome of worker i employed in (2-digit) occupation o and (3-digit) industry j in period t (2004-2009, 2010-15 and 2016-21).

AI_{jt} and Rob_{jt} denote the exposure to AI and robots in 3-digit industry j and period t. The measures are calculated from equation (1) as the cumulative number of AI and robot patents between 1990 and 2006, 2012, or 2018 (standardized with zero mean and a standard deviation of one). Control variables include 2-digit occupation fixed effects (θ_o), 2-digit industry fixed effects (μ_j) and time period fixed effects (δ_t). We further control for the following worker characteristics (X_{it}): worker's education, gender, age, German nationality, firm tenure (0-2 years, 3-5 years, 6-10 years, more than 10 years), firm size (0-9 employees, 10-99, 100-499, 500-999, 1000-9999, more than 10,000), and federal state dummies. To rule out that our results are biased by trade-related product demand shocks, we include changes in net exports during the time period in the industry in which the worker is employed in the base year. All control variables in equation (5) are measured in the base year of each period (i.e., 2004, 2010, or 2016). Standard errors are clustered at the 3-digit industry x period level.

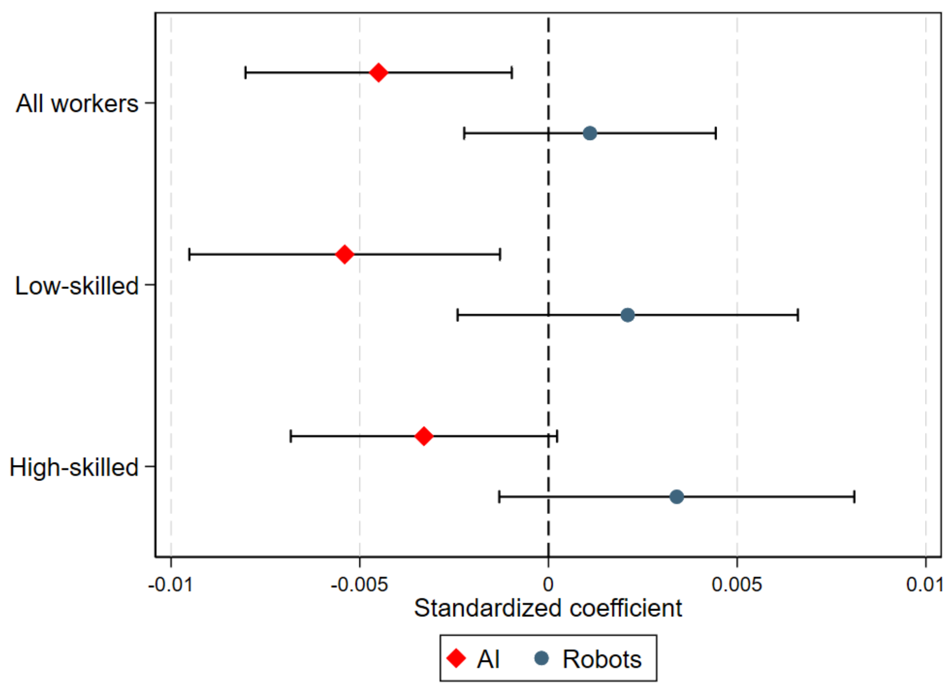
Our main outcomes of interest are employment measured as the cumulative days employed (in logs), earnings measured as cumulative earnings (in logs), and job, occupational, or industry mobility measured by an indicator for switching employer, occupation, or industry during the five-year period. Equation (5) then compares workers who are at the start of the period employed in the same 2-digit occupation and 2-digit industry with similar demographics, region, and labor market history. The parameters of interest (β^{AI} and β^{Rob}) are identified from variation in AI and robot exposure between 3-digit industries within the same 2-digit industry, as well as within 3-digit industries over time among workers with similar observable characteristics.

5.3 Displacement Effects of AI and Robots

We start by assessing the impact of AI and robot exposure on overall employment at the individual worker level. To do so, we estimate equation (5), where the dependent variable is the cumulative days employed during the five-year period following the base year.

Figure 7 plots the effect of AI and robot exposure (by one standard deviation). We find that AI exposure leads to a modest decline in overall employment by about 0.5 percentage points. This displacement effect is about 1/7 of a standard deviation. In contrast, we find no displacement effect of robots, which is again fully in line with previous evidence for Germany. We next distinguish between employment effects for high- and low-skilled workers. AI displaces workers across the skill distribution, with the effect being slightly stronger for low-skilled workers, i.e. those without a university degree. This finding fits the patterns on job tasks, which indicate that AI automates some abstract tasks for all workers, but that low-skilled workers have fewer opportunities to switch to other tasks. The evidence here indicates that AI automation has caused some job losses. Yet, our estimates also find that the adjustment to AI has so far *not* resulted in large-scale displacement at the worker level.

Figure 7: Employment effects of AI and Robots



Notes: The dependent variable is log cumulative days employed over a period of five years. Regressions control for 2-digit industry fixed effects, 2-digit occupation fixed effects, period fixed effects, state fixed effects, demographics (education, age, gender, nationality), tenure, firm size, and the industry-level change in net exports. AI exposure and robot exposure are standardized. High-skilled workers are those with a university degree. Standard errors are clustered at the 3-digit industry x period level.

5.4 AI and Worker Reallocation

Rather than through displacement, a reorganization of production and work processes might require workers to switch jobs within firms. Moreover, the diffusion of AI and robot technologies might require an inflow of new workers with skills that are able to implement or make productive use of the new technologies. Alternatively, workers might leave exposed industries to seek new opportunities in industries that require tasks that are partially automated through AI or robots

We investigate the reallocation of workers in response to exposure to AI and robots in Table 2. Our dependent variables are now whether an individual moves to a new employer or switches the industry of employment or occupation between the base year and the end of the period. The first finding in Table 2 is that AI induces more workers to switch employers (see column (1)). The point estimate indicates that a one standard deviation increase in AI exposure raises the probability of moving to a different firm by 1.4 percentage points. Exposure to robots, in contrast, has the opposite effect, actually reducing worker mobility across firms. The job-stabilizing effect of robots on employment relationships is in line with previous studies for manufacturing industries in Germany (Dauth et al., 2021). Does the higher job mobility also imply that workers switch occupations? Column (2) indicates that the answer is no: workers are not more likely to switch to a different 2-digit occupation if exposed to AI. This result is in line with our findings from the survey data that most of the task changes occur within the same 2- and even 3-digit occupation.

We next ask whether the documented increase in firm mobility occurs mostly within the same industry, e.g. from non-adopting firms to adopting firms, or to firms in non-exposed industries. A second noteworthy result in Table 2 is that workers move mostly to a different employer within the same 2-digit industry (see columns (3) to (5) of Table 2). About half of this mobility occurs between 3-digit industries and the other half within 3-digit industries. Interestingly, column (6) suggests that cross-industry mobility is primarily out of exposed industries and into similar industries that are not (yet) exposed to AI.

Finally, we explore whether workers switching jobs move to 'better-paying' firms. We measure better-paying firms by pre-estimated AKM fixed effects (Abowd et al., 1999), which capture unobserved differences like management quality, efficiency, or market position while holding the composition of the workforce constant. These regressions are based on fewer observations because we do not have AKM firm fixed effects for recently founded firms. It is noteworthy that job mobility occurs in equal shares to higher-paying and lower-paying firms (columns (7) and (8) of Table 2. This last finding suggests that some workers benefit from moving jobs, while others might actually lose a good job match.

Table 2: AI and Job Reallocation

	Firm Change	Occupation Change	Different Industry (3-digit)	Different Industry (2-digit)	Same Industry (2-digit)	Lower AI Exposure Industry	Higher AKM Firm	Lower AKM Firm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI	0.014***	0.001	0.007	0.002	0.013**	0.039***	0.007	0.007*
	(0.005)	(0.008)	(0.005)	(0.004)	(0.005)	(0.008)	(0.004)	(0.004)
Robots	-0.018***	-0.090	-0.019***	-0.017***	0.002	0.000	-0.015***	-0.004
	(0.004)	(0.007)	(0.004)	(0.004)	(0.003)	(0.001)	(0.003)	(0.003)
Mean Y	0.358	0.312	0.241	0.218	0.141	0.087	0.181	0.155
Observations	952,750	952,750	952,750	952,750	952,750	952,750	894,582	894,582

Notes: The dependent variables are indicators for moving to a different firm (1), occupation (2), 3-digit industry (3), 2-digit industry (4), a different firm within the same 2-digit industry (5), an industry with lower AI exposure (6), a firm with higher AKM effect (7), and a firm with lower AKM effect (8). Regressions control for 2-digit industry fixed effects, 2-digit occupation fixed effects, period fixed effects, state fixed effects, demographics (education, age, gender, nationality), tenure, firm size, and the industry-level change in net exports. AI exposure and robot exposure are standardized. Standard errors are clustered at the 3-digit industry x period level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

5.5 Impact of AI and Robots on Earnings

The results in the previous subsections indicate that AI has resulted in worker reallocation in addition to some job displacement. We find little evidence that AI exposure increases occupational mobility. These patterns support our conclusion from the task data that adjustments to the new technologies have occurred primarily through changes in job tasks within the same occupation. Workers in exposed industries thus see the content of their jobs change, while workers in the same occupation in non-exposed industries have not seen much pressure to adapt. The effects on either margin are still modest but have real consequences for the exposed workers. We now explore whether the observed adjustments to AI are also reflected in worker earnings.

To do so, we re-estimate equation (5) where the dependent variable is now the cumulative earnings of the worker over the 5-year period. Figure 8 indicates that earnings slightly *decrease* for workers exposed in their job to AI. The estimate indicates that increasing AI exposure by one standard deviation reduces earnings by about 1.2 percentage points over a five-year period. While the overall effect is modest, Figure 8 further shows that AI hits the earnings of low-skilled workers harder than those of high-skilled workers. The estimates indicate that the earnings of low-skilled workers decline by 2.5 percentage points if exposure to AI increases by a standard deviation, while we see no statistically significant effect for high-skilled earnings.

Based on the job reallocation results in the previous section, we next ask whether the observed changes in earnings are related to worker mobility. These estimates are obtained by comparing job movers in exposed industries to job movers in non-exposed industries controlling for a large set of other confounding factors. Yet, we consider these estimates to be suggestive, as unobservable determinants of job mobility may differ across industries for reasons other than AI exposure. Nevertheless, we find the exercise insightful for understanding which workers might lose from the diffusion of AI. The bottom part in Figure 8 indicates that low-skilled workers see their earnings decline when they remain in their job, but also if they move to a different job. One possible interpretation of this pattern is that low-skilled workers have mostly been affected by automation with few gains from productivity gains, switching to different tasks or seeking outside options in a different job. The fact that job mobility is associated with lower earnings likely indicates that job mobility among low-skilled workers is, at least in part, involuntary.

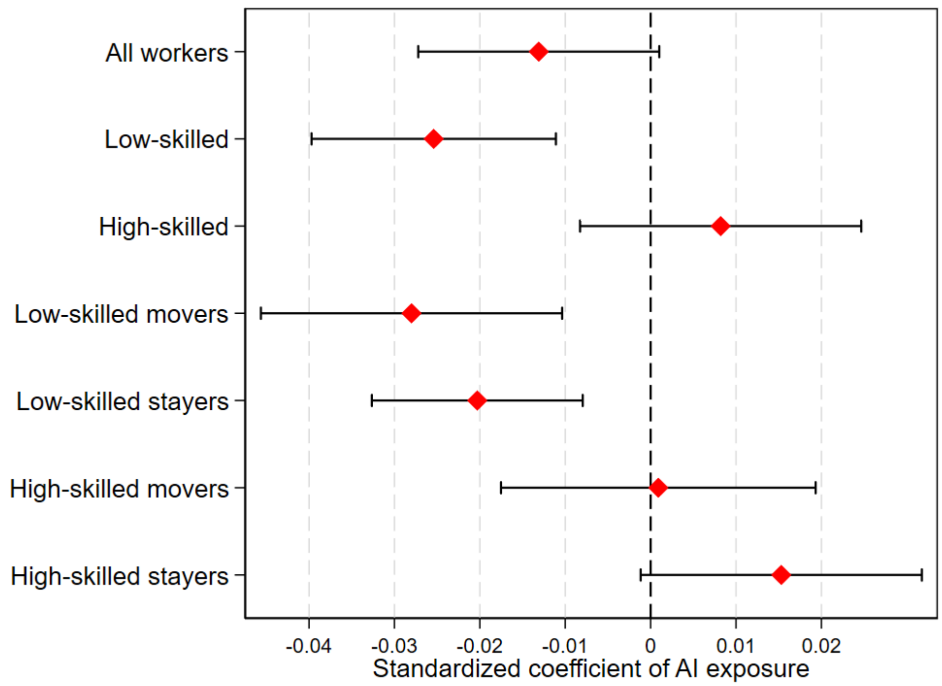
The picture looks very different for high-skilled workers. High-skilled workers who remain in their jobs in exposed industries see their earnings increase by around 1.5 percentage points. Unlike low-skilled workers, high-skilled workers might thus benefit from productivity gains or even new tasks associated with AI. The average effect on movers is zero suggesting that some high-skilled workers manage to improve their job match while others lose a good match. Even if high-skilled workers switch jobs, they do not suffer earnings losses, while low-skilled workers lose. Overall, our findings suggest that high-skilled workers are more likely to benefit from changes in AI than low-skilled workers.

We demonstrate that these findings on employment, reallocation, and earnings are highly robust to alternative specifications of the exposure measures or the timing of the effects in Appendix Figures A.5 and A.6 as well as Appendix Table A.9. The patterns are qualitatively and quantitatively very similar to the baseline results.

6 Conclusion

This paper shows that AI has already shifted the task content of jobs in Germany. Using a new measure of industry-level exposure to AI and robot technologies based on patent data, we have five main findings. First, we document that AI has decreased the abstract task share in jobs, in particular in the category of gathering information and documentation. In contrast, AI has increased the need for high-level routine tasks in monitoring processes, which require the use of

Figure 8: Impact of AI on Earnings



Notes: The dependent variable is log cumulative earnings over a period of five years. Regressions control for 2-digit industry fixed effects, 2-digit occupation fixed effects, period fixed effects, state fixed effects, demographics (education, age, gender, nationality), tenure, firm size, and the industry-level change in net exports. AI exposure and robot exposure are standardized. High-skilled workers are those with a university degree. Movers are those who leave their initial firm (in the base year) during the following 5-year-period; stayers remain employed at the initial firm throughout the period. Standard errors are clustered at the 3-digit industry x period level.

a computer or tablet. Most of the changes occur within detailed occupations, indicating that AI shifts the assignment of tasks to workers. These effects become more pronounced as the capabilities of AI expand over time.

Second, AI's impact on job tasks differs sharply from that of robots, which increased the demand for abstract tasks and reduced the demand for routine tasks. This observation challenges the view that AI continues previous technological trends of automating mostly routine tasks. Indeed, the evidence indicates that AI can take over non-routine tasks that push the boundary of what machines can do further toward complex tasks. Third, the changes brought about by AI are not skill-neutral. Low-skilled workers in AI-exposed industries switch from abstract to routine tasks, mirroring the overall changes. High-skilled worker, in contrast, can leverage their comparative advantage by switching from information gathering to educating and training as well. Hence, while both skill groups are affected by the automation of abstract tasks (information gathering), high-skilled workers can more easily switch to performing other abstract tasks like training and educating.

We then turn to administrative social security data to understand the consequences for worker careers. Our fourth result is that AI has so far not displaced many workers. Instead, workers have responded to AI by switching employers. About half of the job mobility is within industry, while the other half is into similar, but different industries that are less exposed to AI. The AI-induced reallocation differs from that of robots, which stabilized jobs with the same employer but increased occupational switches. Finally, we document that the reassignment of tasks across workers reduces the wages of low-skilled workers in exposed industries –irrespective of whether they switch jobs or not. This modest decline in wages suggests that for low-skilled workers, the loss from automation exceeds any productivity gains in Germany at the dawn of the AI age. In contrast, high-skilled workers benefit on average from productivity gains and their comparative advantage in tasks if they remain in their jobs. Our results highlight that if the diffusion of AI is dominated by automation concerns, this can lead to wage losses for some workers.

While the magnitude of the employment and wage changes are still modest, the patterns suggest that AI has profound impacts on job content, task assignment, and the productivity of different skill groups. Most importantly, the observed changes benefit some workers but reduce the earnings of others. Moreover, the observed patterns differ a lot from those of earlier waves of technology, in particular the diffusion of robots. As AI continues to evolve and diffuse into more industries and occupations, policy-makers need to direct training and re-skilling measures to strengthen labor's comparative advantage and encourage worker mobility to increase benefits from AI advancements.

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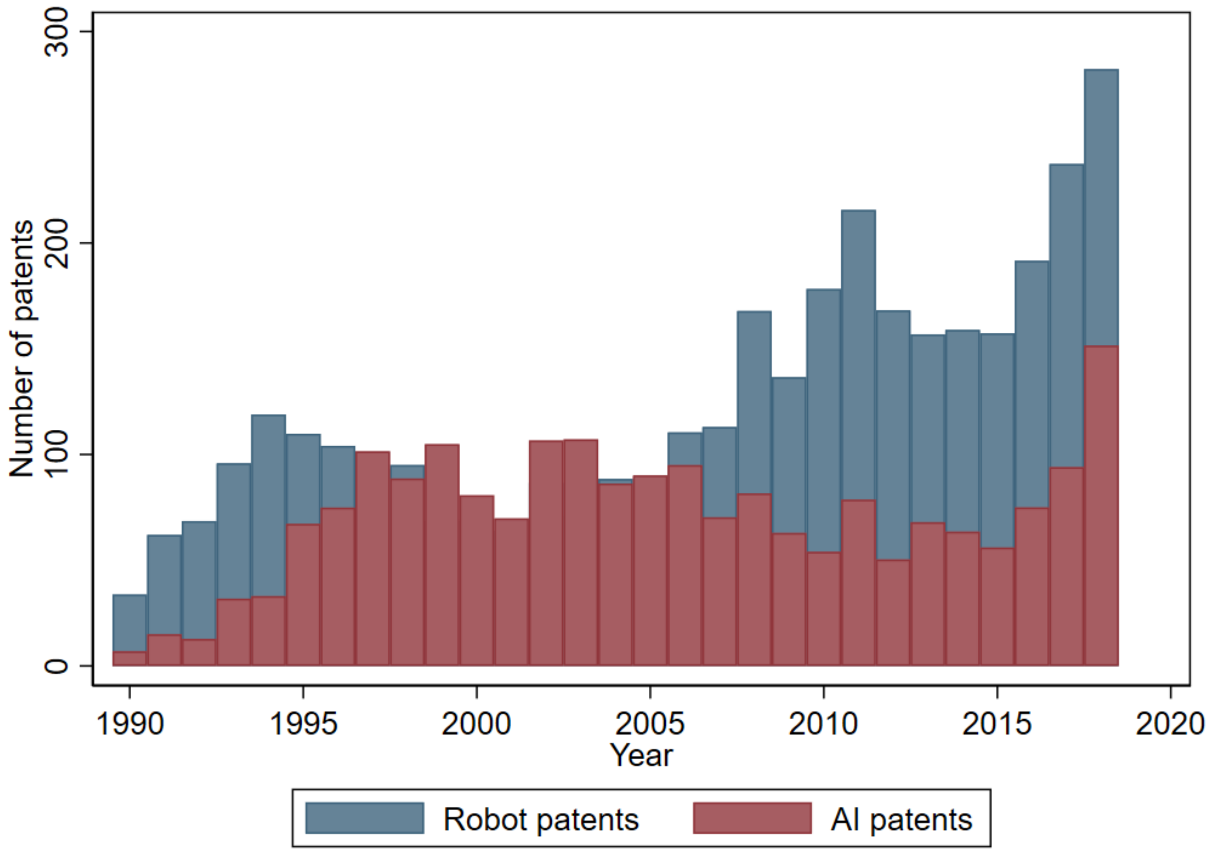
A Appendix

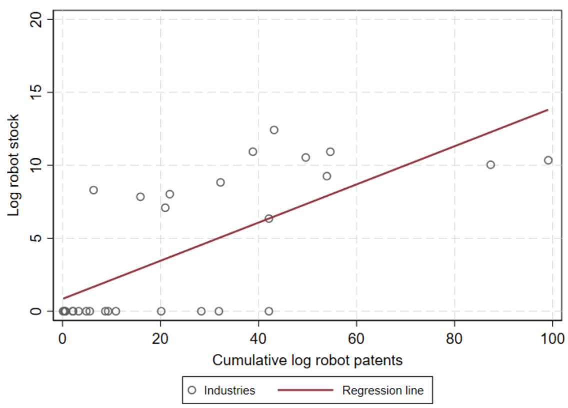
Figure A.1: Evolution of AI and Robot Patents over Time



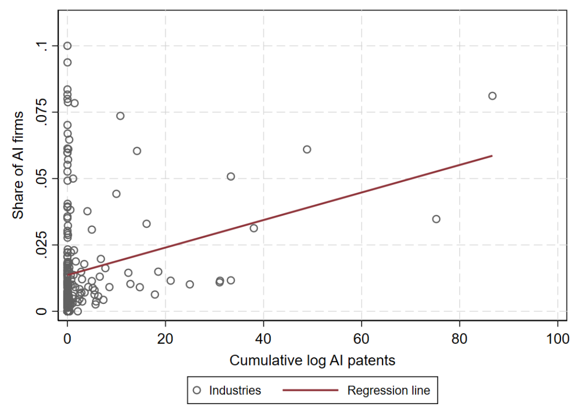
Notes: The figure shows the number of AI and robot patent grants per year between 1990 and 2018.

Figure A.2: Link between patents and other measures

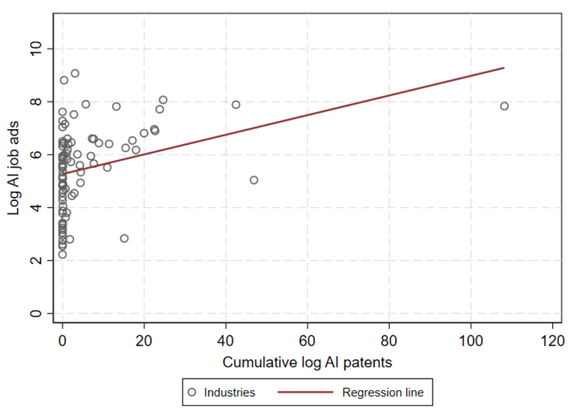
A: Robot patents and robot stock (2-digit)



B: AI patents and AI firms (3-digit)

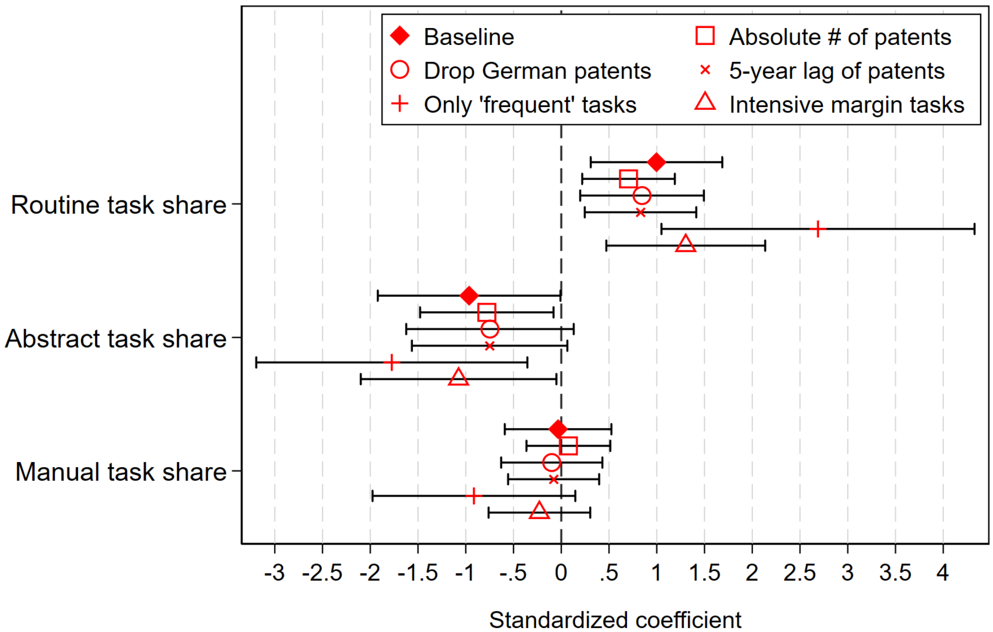


C: AI patents and AI vacancies (2-digit)

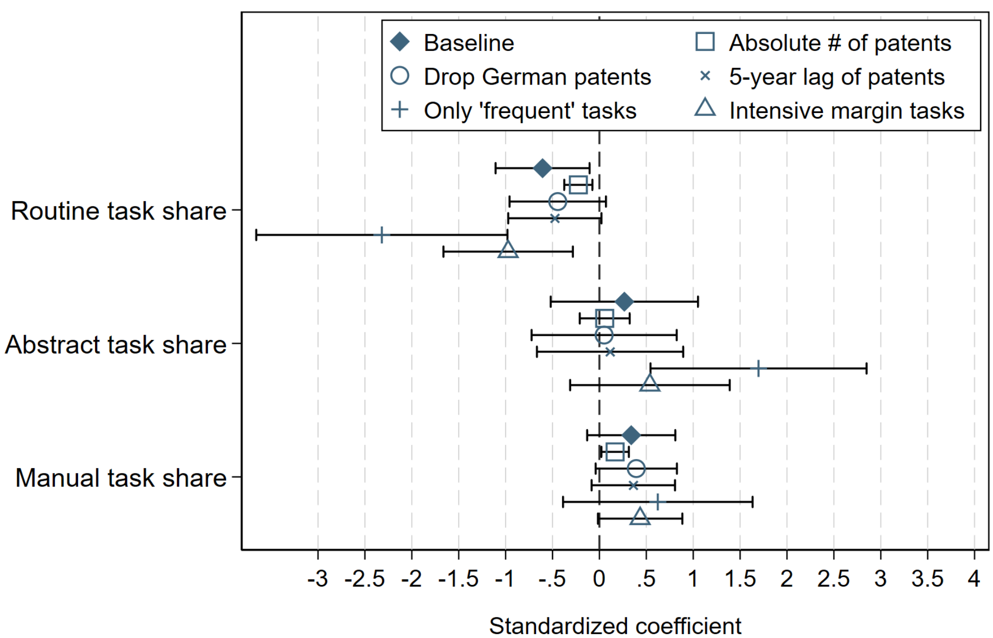


Notes: The figures show the correlation of our AI and robot exposure measures with other proxies for AI and robots. The exposure measures are based on patents in the specific technologies and measured as cumulative sum of log patent grants until 2018. Panel A shows the correlation between our robot patent measure and the stock of industrial robots in 2018 (based on International Federation of Robotics (2021)). Panel B exhibits the correlation between our AI patent measure and the share of firms using or developing AI in Germany in 2022 (based on data from company websites from *Istari.ai*). Panel C shows the correlation between our AI patent measure and the number of vacancies that require at least one AI skill (based on online job vacancy data for Germany in 2021).

Figure A.3: Robustness: AI and Robots and Job Tasks



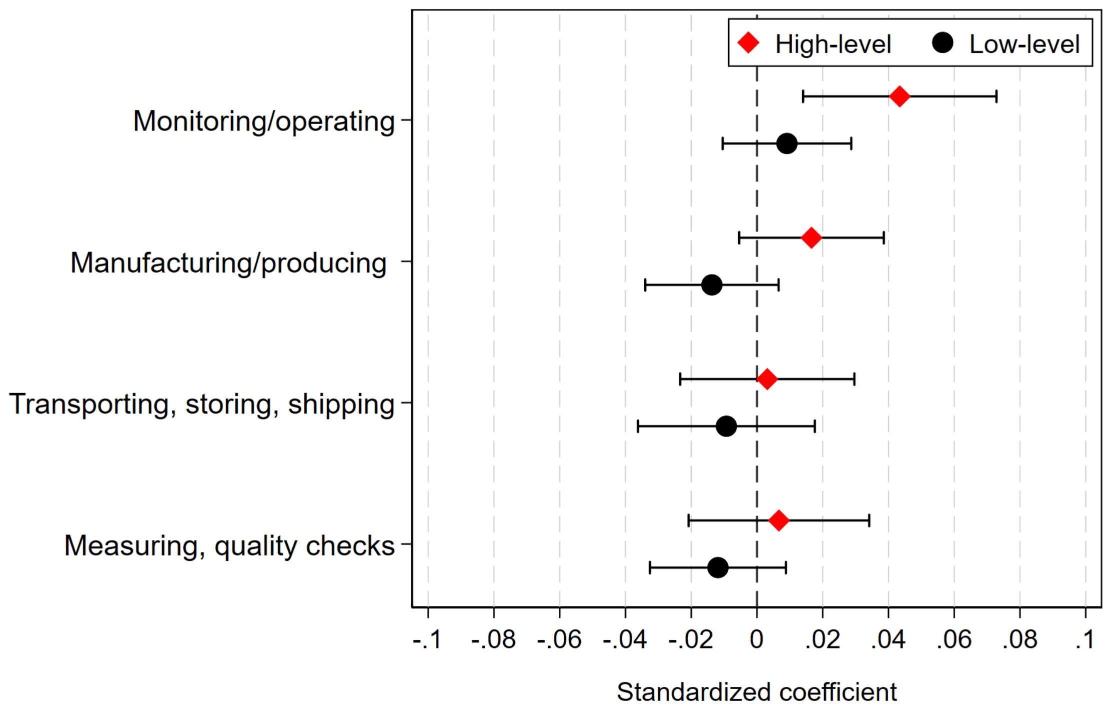
(a) AI



(b) Robots

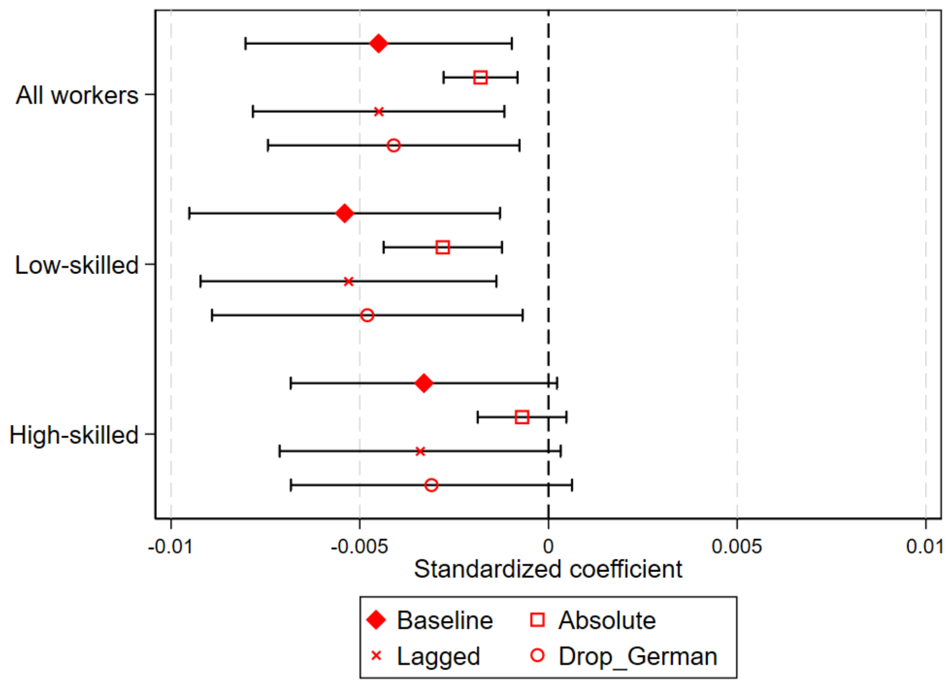
Notes: The figure shows estimates of robustness tests in which we use the absolute number of patents (square), drop German patents (circle), use a 5-year lag of patent exposure (x), code tasks as 1 if performed frequently and 0 otherwise (+), assign a value of 2 if a task is performed frequently, 1 if it is performed occasionally, and 0 otherwise (triangle).

Figure A.4: Robustness: AI and Low- versus High-Level Routine Tasks



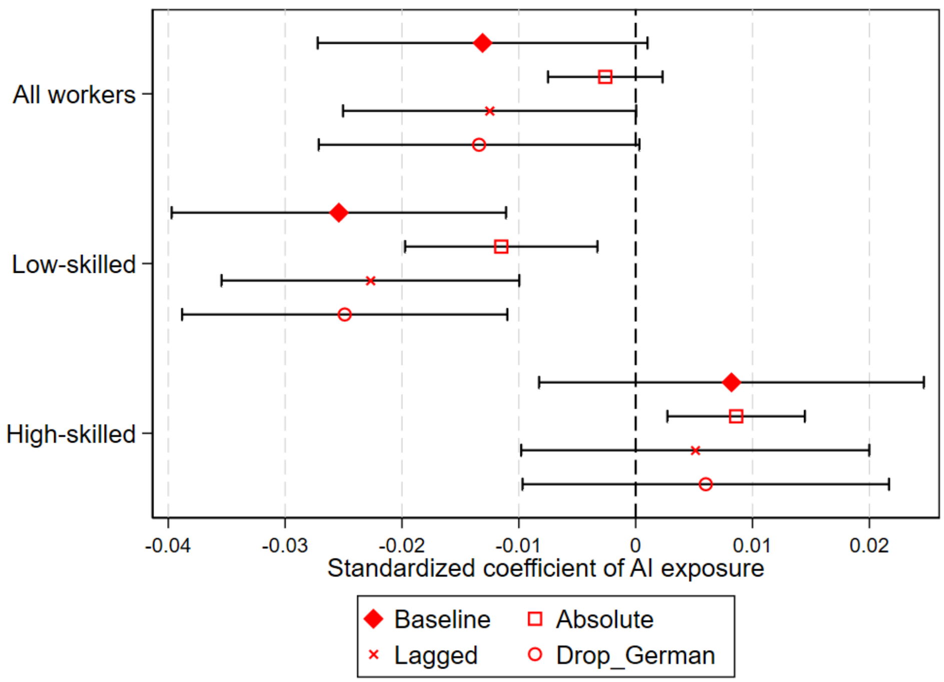
Notes: The figure shows the impact of AI exposure (by one standard deviation) on the probability of performing a specific routine task. We define a routine task as 'low-level' if a worker also reports that the execution of his work is often prescribed down to the last detail. In contrast, we define a routine task as 'high-level' if a worker reports that the execution of his work is not often prescribed down to the last detail. The estimation is based on equation (4) including all controls.

Figure A.5: Robustness: Employment effects of AI and Robots



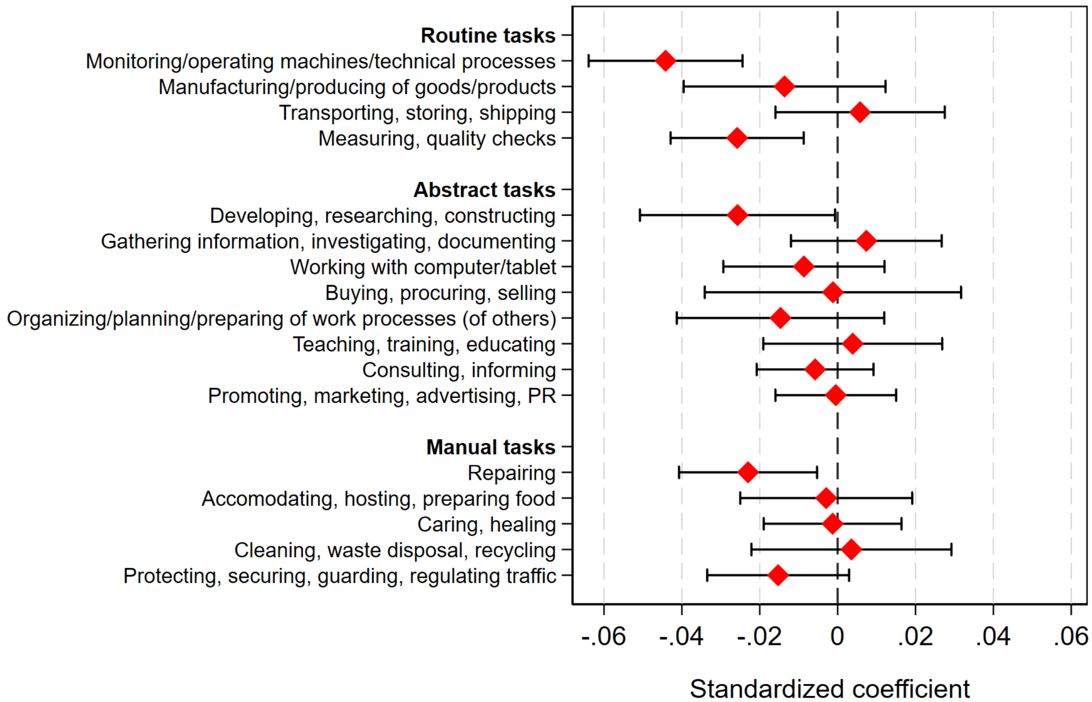
Notes: The dependent variable is log cumulative days employed over a period of five years. Regressions control for 2-digit industry fixed effects, 2-digit occupation fixed effects, period fixed effects, state fixed effects, demographics (education, age, gender, nationality), tenure, firm size, and the industry-level change in net exports. AI exposure and robot exposure are standardized. High-skilled workers are those with a university degree. Standard errors are clustered at the 3-digit industry x period level.

Figure A.6: Robustness: Impact of AI on Earnings



Notes: The dependent variable is log cumulative earnings over a period of five years. Regressions control for 2-digit industry fixed effects, 2-digit occupation fixed effects, period fixed effects, state fixed effects, demographics (education, age, gender, nationality), tenure, firm size, and the industry-level change in net exports. AI exposure and robot exposure are standardized. High-skilled workers are those with a university degree. Movers are those who leave their initial firm (in the base year) during the following 5-year-period; stayers remain employed at the initial firm throughout the period. Standard errors are clustered at the 3-digit industry x period level.

Figure A.7: Robots and Detailed Job Tasks



Notes: The figure shows the relationship between robot exposure and the probability to perform a single task (measured in percent). Regressions include 2-digit industry, 2-digit occupation and period dummies, demographic controls (education, gender, age groups (18-25, 26-35, 36-45, 46-55, 56-65), German nationality) and federal state dummies. Regressions employ sample weights. Standard errors are clustered at industry-year level. the lines reflect 95% confidence intervals.

Table A.1: Industries with the Highest Number of AI and Robot Patents

	Number of Patents (1990-2018)
Panel A: AI Patents	
Manufacture of computers and peripheral equipment	643.0
Manufacture of consumer electronics	405.2
Manufacture of communication equipment	147.1
Manufacture of measuring, testing, navigating and control equipment	92.2
Manufacture of optical instruments and photographic equipment	75.26
Manufacture of general-purpose machinery	72.00
Motion picture, video and television program activities	69.7
Sound recording and music publishing activities	65.7
Manufacture of special-purpose machinery	52.4
Medical and dental practice activities	46.5
Panel B: Robot Patents	
Manufacture of general-purpose machinery	718.4
Manufacture of special-purpose machinery	275.5
Manufacture of other fabricated metal products, metalworking activities	167.9
Manufacture of domestic appliances	161.5
Manufacture of measuring, testing, navigating and control equipment	157.6
Manufacture of computers and peripheral equipment	147.5
Manufacture of optical instruments and photographic equipment	131.0
Manufacture of dairy products	130.5
Medical and dental practice activities	100.5
Manufacture of basic iron and steel	99.2

Notes: The table shows the industries (ISIC rev.4, 3-digit level) with the largest cumulative number of AI (Panel A) and robot (Panel B) patents from 1990 to 2018, respectively.

Table A.2: Descriptives of Task Data

	All years	2006	2012	2018
	(1)	(2)	(3)	(4)
Panel A: Task Groups				
	mean/sd	mean/sd	mean/sd	mean/sd
Routine task share (%)	23.70	23.89	24.11	23.08
	(15.09)	(15.69)	(14.91)	(14.62)
Abstract task share (%)	57.21	56.27	57.01	58.38
	(22.22)	(22.97)	(21.92)	(21.66)
Manual task share (%)	19.10	19.84	18.88	18.55
	(14.36)	(14.86)	(14.09)	(14.06)
Panel B: Detailed Tasks				
	mean/sd	mean/sd	mean/sd	mean/sd
Monitoring/operating machines/technical processes	0.50	0.50	0.51	0.49
	(0.50)	(0.50)	(0.50)	(0.50)
Manufacturing/producing of goods/products	0.28	0.28	0.30	0.26
	(0.45)	(0.45)	(0.46)	(0.44)
Transporting, storing, shipping	0.54	0.55	0.55	0.53
	(0.50)	(0.50)	(0.50)	(0.50)
Measuring, quality checks	0.75	0.73	0.77	0.76
	(0.43)	(0.44)	(0.42)	(0.43)
Developing, researching, constructing	0.37	0.36	0.37	0.39
	(0.48)	(0.48)	(0.48)	(0.49)
Gathering information, investigating, documenting	0.81	0.79	0.81	0.83
	(0.39)	(0.41)	(0.39)	(0.37)
Promoting, marketing, advertising, PR	0.35	0.36	0.35	0.34
	(0.48)	(0.48)	(0.48)	(0.47)
Organizing/planning/preparing of work processes (of others)	0.71	0.67	0.70	0.76
	(0.45)	(0.47)	(0.46)	(0.43)
Teaching, training, educating	0.59	0.57	0.60	0.60
	(0.49)	(0.50)	(0.49)	(0.49)
Consulting, informing	0.85	0.86	0.85	0.85
	(0.35)	(0.35)	(0.35)	(0.35)
Buying, procuring, selling	0.41	0.41	0.41	0.41
	(0.49)	(0.49)	(0.49)	(0.49)
Working with computer/tablet	0.82	0.79	0.83	0.85
	(0.38)	(0.40)	(0.37)	(0.36)
Repairing	0.49	0.50	0.49	0.48
	(0.50)	(0.50)	(0.50)	(0.50)
Accomodating, hosting, preparing food	0.16	0.16	0.15	0.17
	(0.37)	(0.36)	(0.36)	(0.38)
Caring, healing	0.22	0.23	0.21	0.21
	(0.41)	(0.42)	(0.41)	(0.41)
Protecting, securing, guarding, regulating traffic	0.40	0.41	0.39	0.40
	(0.49)	(0.49)	(0.49)	(0.49)
Cleaning, waste disposal, recycling	0.52	0.51	0.53	0.51
	(0.50)	(0.50)	(0.50)	(0.50)
Observations	37,415	12,754	12,229	12,432

Notes: The table shows the mean and standard deviation (in brackets) for task shares of the three task groups (Panel A) and detailed tasks (Panel B). Column (1) shows the descriptives for all years, columns (2) to (4) for each survey wave (2006, 2012, and 2018) separately.

Table A.3: Top occupations performing individual tasks (part 1)

Occupation	Share
Manufacturing/producing of goods/products	
Occupations in leather- and fur-making and -processing	.979
Occupations in metalworking	.897
Occupations in plastic- and rubber-making and -processing	.863
Measuring, quality checks	
Occupations in metalworking	.974
Occupations in physics	.974
Occupations in mechatronics, automation and control technology	.972
Monitoring/operating machines/technical processes	
Aircraft pilots	.980
Drivers of vehicles in railway traffic	.973
Occupations in metalworking	.946
Transporting, storing, shipping	
Driver of vehicles in road traffic	.960
Occupations in warehousing and logistics, delivery services, cargo handling	.932
Occupations in animal care	.885
Developing, researching, constructing	
Teachers and researcher at universities and colleges	.940
Draftspersons, technical designers, and model makers	.926
Occupations in software development and programming	.924
Gathering information, investigating, documenting	
Occupations in pharmacy	1.000
Occupations providing nutritional advice or health counselling, wellness	1.000
Occupations in biology	1.000
Working with Computer/Tablet	
Occupations in human resources management and personnel service	1.000
Driving, flying and sports instructors at educational institutions other than schools	1.000
Occupations in accounting, controlling and auditing	1.000
Buying, procuring, selling	
Occupations in body care	.961
Occupations in floristry	.933
Sales occupations (retail) selling drugstore products, pharmaceuticals, medical supplies	.928
Organizing/planning/preparing work processes (of others)	
Occupations in theatre, film and television productions	1.000
Occupations in event organisation and management	.974
Managing directors and executive board members	.951
Teaching, training, educating	
Teachers in schools of general education	.999
Teachers for occupation-specific subjects in-company instructors	.994
Driving, flying and sports instructors at other educational institutions	.978

Notes: The table shows for each individual task the top three occupations which exhibit the highest share of workers performing the respective task.

Table A.4: Top occupations performing individual tasks (part 2)

Occupation	Share
Consulting, informing	
Legislators and senior officials of special interest organisations	1.000
Occupations in public relations	1.000
Occupations in non-medical therapy and alternative medicine	1.000
Promoting, marketing, advertising, PR	
Occupations in public relations	.995
Legislators and senior officials of special interest organisations	.904
Managing directors and executive board members	.869
Repairing	
Occupations in building services engineering	.960
Occupations in plumping, sanitation, heating, ventilating, and air conditioning	.940
Conditioning and processing of natural stone and minerals, production of building materials	.939
Accomodating, hosting, preparing food	
Cooking occupations	.935
Gastronomy occupations	.889
Occupations in geriatric care	.872
Caring, healing	
Occupations in geriatric care	.988
Occupations in nursing, emergency medical services and obstetrics	.970
Occupations in human medicine and dentistry	.951
Cleaning, waste disposal, recycling	
Occupations in animal care	.954
Occupations in housekeeping and consumer counselling	.921
Sales occupations (retail) selling foodstuffs	.906
Protecting, securing, guarding, regulating traffic	
Occupations in the inspection and maintenance of traffic infrastructure	.894
Occupations in physical security, personal protection, fire protection and workplace safety	.881
Armed forces personnel in other ranks	.850

Notes: The table shows for each individual task the top three occupations which exhibit the highest share of workers performing the respective task.

Table A.5: Technology and Worker-level Task Shares

Panel A: Routine tasks (%)	(1)	(2)	(3)
AI	1.266***	1.185***	0.998***
	(0.303)	(0.278)	(0.351)
Robots	-0.882**	-0.889***	-0.606**
	(0.354)	(0.305)	(0.256)
Mean of Y variable	23.695	23.695	23.695
R^2	0.197	0.244	0.370

Panel B: Abstract tasks (%)	(1)	(2)	(3)
AI	-1.436***	-1.278***	-0.964**
	(0.435)	(0.393)	(0.488)
Robots	0.545	0.555	0.266
	(0.580)	(0.511)	(0.401)
Mean of Y variable	57.207	57.207	57.207
R^2	0.201	0.311	0.499

Panel C: Manual tasks (%)	(1)	(2)	(3)
AI	0.170	0.092	-0.033
	(0.287)	(0.274)	(0.285)
Robots	0.337	0.334	0.340
	(0.305)	(0.296)	(0.240)
Mean of Y variable	19.097	19.097	19.097
R^2	0.146	0.233	0.367
Industry & year FE	X	X	X
Demographic controls		X	X
State FE		X	X
2-digit occupation FE			X

Notes: The dependent variables are the task shares in year t measured in percent: routine tasks (Panel A), abstract tasks (Panel B) and manual tasks (Panel C). The AI and robot exposure measures are defined in equation (1). All columns control for 2-digit industry and year dummies. Column (2) adds demographic controls, which include education, gender, age groups (18-25, 26-35, 36-45, 46-55, 56-65), German nationality, and federal state dummies. Column (3) adds 2-digit occupation fixed effects. Number of observations: 37,415. Standard errors clustered at industry-year level are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.6: Comparing the Effects across Time

Panel A: Routine tasks	2006	2012	2018
	(1)	(2)	(3)
AI	0.412	0.616**	0.913***
	(0.418)	(0.296)	(0.203)
Robots	-0.456	-0.510	-0.913***
	(0.451)	(0.317)	(0.205)
Mean Y	23.892	24.112	23.077
R2	0.358	0.374	0.371
Panel B: Abstract tasks	2006	2012	2018
	(1)	(2)	(3)
AI	-0.297	-0.323	-0.882***
	(0.610)	(0.585)	(0.231)
Robots	0.925	0.434	0.899***
	(0.604)	(0.507)	(0.235)
Mean Y	56.272	57.006	58.378
R2	0.498	0.501	0.494
Panel C: Manual tasks	2006	2012	2018
	(1)	(2)	(3)
AI	-0.115	-0.294	-0.031
	(0.263)	(0.365)	(0.119)
Robots	-0.469**	0.075	0.014
	(0.228)	(0.262)	(0.145)
Mean Y	19.837	18.882	18.545
R2	0.358	0.370	0.373

Notes: The dependent variables are routine tasks (Panel A), abstract tasks (Panel B) and manual tasks (Panel C) in year t measured in percent. The AI and robot exposure measures are defined in equation (**??**). All columns control for 2-digit industry, 2-digit occupation and year fixed effects, demographics (education, gender, age groups, German nationality) and federal state dummies. Standard errors are clustered at industry-level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.7: Top occupations performing high-level and low-level routine tasks

Occupation	Share
High-level Monitoring/operating machines/technical processes	
Aircraft pilots	.980
Laboratory occupations in medicine	.884
Occupations in physics	.882
Low-level Monitoring/operating machines/technical processes	
Occupations in gardening	.523
Occupations in building construction	.505
Occupations in civil engineering	.500
High-level Measuring, quality checks	
Occupations in physics	.974
Aircraft pilots	.966
Occupations in mechatronics, automation and control technology	.957
Low-level Measuring, quality checks	
Occupations in building construction	.750
Floor layers	.622
Painters and varnishers, plasterers, occupations in the waterproofing of buildings	.618
High-level Manufacturing/producing of goods/products	
Occupations in metalworking	.778
Occupations in industrial glass-making and -processing	.726
Occupations in precision mechanics and tool making	.726
Low-level Manufacturing/producing of goods/products	
Occupations in leather- and fur-making and -processing	.525
Occupations in the production of clothing and other textile products	.480
Occupations in floristry	.402
High-level Transporting, storing, shipping	
Sales occupations (retail) selling drugstore products, pharmaceuticals	.817
Occupations in pharmacy	.720
Doctors' receptionists and assistants	.713
Low-level Transporting, storing, shipping	
Occupations in building construction	.615
Painters and varnishers, plasterers, occupations in the waterproofing of buildings	.611
Floor layers	.608

Notes: The table shows for each individual (high-level and low-level) routine task the top three occupations which exhibit the highest share of workers performing the respective task.

Table A.8: Descriptive Statistics of Social Security Data (SIAB)

	Mean	Std. Dev.	25th Perc.	75th Perc.
Cumulative earnings	207,332.31	141,146.81	119,514.76	251,035.69
Log cumulative earnings	12.01	0.74	11.69	12.43
Cumulative days employed	1,648.78	349.28	1665.00	1826.00
Log cumulative days employed	7.37	0.35	7.42	7.51
University degree	0.18	0.38	0.00	0.00
Vocational degree	0.75	0.43	1.00	1.00
Low-skilled	0.07	0.26	0.00	0.00
Female	0.34	0.47	0.00	0.00
German nationality	0.93	0.25	1.00	1.00
Age	39.62	9.49	32.00	48.00
Tenure 0-2 years	0.29	0.45	0.00	1.00
Tenure 3-5 years	0.24	0.43	0.00	0.00
Tenure 6-10 years	0.21	0.41	0.00	0.00
Tenure $>$ 10 years	0.26	0.44	0.00	1.00
Plant size 0-9	0.13	0.33	0.00	0.00
Plant size 10-99	0.37	0.48	0.00	1.00
Plant size 100-499	0.27	0.44	0.00	1.00
Plant size 500-999	0.08	0.28	0.00	0.00
plant size 1,000-9,999	0.12	0.33	0.00	0.00
plant size $>=$ 10,000	0.02	0.15	0.00	0.00
Δ Net Exports	0.00	1.00	-0.12	0.22

Notes: The table shows selected descriptive statistics of our sample using Social Security Data. Cumulative earnings and employment are computed over 5 years following the base years 2004, 2010, and 2016. Δ *Net Exports denotes the change in net exports during the time window in the 3-digit industry in which the worker is employed in the base year. All other variables are measured in the base year. N=952,750.*

Table A.9: Robustness: AI and Job Reallocation

	Firm Change	Occupation Change	Different Industry (3-digit)	Different Industry (2-digit)	Same Industry (2-digit)	Lower AI Exposure Industry	Higher AKM Firm	Lower AKM Firm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baseline	0.014***	0.001	0.007	0.002	0.013**	0.039***	0.007	0.007*
	(0.005)	(0.008)	(0.005)	(0.004)	(0.005)	(0.008)	(0.004)	(0.004)
Absolute number	0.007**	-0.0015	0.006*	0.002	0.005*	0.015***	0.003	0.004**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)
3-year-lag	0.013***	0.002	0.006	0.001	0.012**	0.033***	0.007*	0.006*
	(0.004)	(0.008)	(0.004)	(0.004)	(0.005)	(0.007)	(0.004)	(0.003)
Drop German patents	0.014***	0.002	0.007	0.002	0.012**	0.037***	0.007*	0.006*
	(0.005)	(0.008)	(0.005)	(0.004)	(0.005)	(0.007)	(0.004)	(0.003)
Mean Y	0.358	0.312	0.241	0.218	0.141	0.087	0.181	0.155
Observations	952,750	952,750	952,750	952,750	952,750	952,750	894,582	894,582

Notes: The dependent variables are indicators for moving to a different firm (1), occupation (2), 3-digit industry (3), 2-digit industry (4), a different firm within the same 2-digit industry (5), an industry with lower AI exposure (6), a firm with higher AKM effect (7), and a firm with lower AKM effect (8). Regressions control for 2-digit industry FEs, 2-digit occupation FEs, period FEs, state FEs, demographics (education, age, gender, nationality), tenure, firm size, and the industry-level change in net exports. AI exposure and robot exposure are standardized. Standard errors are clustered at the 3-digit industry x period level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.