Essays on the Labor Market Effects of Digitalisation

Inauguraldissertation zur Erlangung des Doktorgrades
des Fachbereichs Wirtschaftswissenschaften der
Ruprecht-Karls-Universität Heidelberg

vorgelegt von
Felix Grimm

Heidelberg
Juni 2024

Acknowledgements

This thesis was written at the University of Heidelberg and the Luxembourg Institute of Socio-Economic Research and has benefited immensely from the support of many people.

First, I want to thank my advisor, Christina Gathmann, for her continuing support during this project. I am thankful for her active collaboration on two of the papers included in this thesis and for her guidance and advice on my single-author paper.

Next, I thank Melanie Arntz for being my second supervisor and part of the dissertation committee.

The first and second chapters of this thesis are coauthored, and I want to thank Christina and Erwin for their great collaboration.

I was lucky to have amazing colleagues in Heidelberg and Luxembourg who became friends along the way. It was great sharing an office with Matthias and Julio, even if the last one didn't have a window. Thanks also to David for always welcoming me to his office after I left Heidelberg. Thanks to Anna and Sabine for helping me through the uncertainties of my move to Luxembourg and to Gaspare for always having an open ear for the frustrations of a project like this.

I also want to thank my friends at Heidelberger Straße for taking my mind off work when necessary and enjoying life in Heidelberg. I will never forget the great times we had living together. I do hope to forget some of the cleaning issues, though.

This thesis would not have been possible without the support of my family, and I am beyond grateful to them for always believing in me and giving me the freedom to pursue my goals.

Finally, thank you, Lau, for being by my side on our journey across two continents and three countries. Your love, support, and understanding made this possible.

Contents

List of Figures **vii**

List of Tables **viii**

1 Introduction **1**

1.1 Labor Market Effects of AI and Robotics 5
1.2 AI and the Task Content of Occupations 6
1.3 Digital Technologies, Job Quality and Employer-provided Training 7

2 Labor Market Effects of Artificial Intelligence and Robotics **11**

2.1 Patent-based Measures of AI and Robotics for Europe 16
2.1.1 European Patent Data 17
2.1.2 Identifying Patents in Robotics and AI 17
2.1.3 Robotics and AI Technologies at the Industry Level 19
2.2 Technology Exposure and Technology Use 21
2.2.1 Defining the Exposure Measure 21
2.2.2 Robotics Patents and Robot Installations 22
2.2.3 AI Patents, AI Firm Share and AI Job Vacancies 23
2.3 Administrative Plant-level Data 24
2.4 AI and Robots: Plant-level Evidence 25
2.4.1 Estimation Approach at the Plant Level 25
2.4.2 Employment and Wage Effects at the Plant Level 27
2.4.3 Skill Bias of AI and Robots 28
2.5 AI and Robotics Technologies: Effects on Local Labor Markets . . . 29
2.5.1 Estimation Approach at the Local Labor Market 29
2.5.2 Local Employment and Wages 31
2.5.3 Manufacturing versus Services 32
2.5.4 Skill Bias of AI and Robots at the Local Level 33
2.6 Robustness Checks 35
2.7 Conclusion 36
2.A Details on Construction of Patent Measures 39

2.B Figures . . . 42
2.C Tables . . . 49
2.D Additional Results . . . 54

3 Artificial Intelligence and the Task Content of Occupations 63
3.1 Measuring Advances in AI and Robotics . . . 68
3.2 AI and Tasks Performed on the Job . . . 71
3.2.1 Data on Tasks Performed on the Job . . . 71
3.2.2 Empirical Strategy . . . 73
3.2.3 Do Tasks Predict Future Exposure? . . . 73
3.3 AI and Changes in Job Tasks . . . 75
3.3.1 Industry-level Correlations . . . 75
3.3.2 AI, Robots and Worker-level Tasks . . . 77
3.3.3 Heterogeneity by Skill and Age . . . 82
3.3.4 Robustness Checks . . . 85
3.4 AI and Job Reallocation . . . 87
3.4.1 Administrative Labor Market Data . . . 88
3.4.2 Empirical Strategy . . . 88
3.4.3 Impact on Employment and Earnings . . . 89
3.4.4 Worker Reallocation . . . 90
3.4.5 Differences between Occupations . . . 92
3.4.6 Heterogeneity by Skill and Age . . . 93
3.5 Conclusion . . . 95
3.A Figures . . . 97
3.B Tables . . . 100

4 Digital Technologies, Job Quality and Employer-provided Training 103
4.1 Data . . . 107
4.1.1 Linked Personnel Panel . . . 108
4.1.2 Measures for Digital Technology Exposure . . . 109
4.2 Empirical Strategy . . . 114
4.3 Results: Working Conditions and Training . . . 118
4.3.1 Results by Age and Gender . . . 125
4.3.2 Training and Personnel Management as Mitigating Factors . 127
4.3.2.1 Employer-provided Training . . . 127
4.3.2.2 Personnel Management . . . 128
4.4 Additional Results: Well-being and Health . . . 129
4.5 Robustness Checks . . . 130
4.6 Conclusion . . . 132

4.A Additional Tables 134

Bibliography **145**

List of Figures

2.B.1 Number of Patents in AI and Robotics, 1990-2018 42
2.B.2 Cumulative log AI patents by industry 43
2.B.3 Cumulative log robot patents by industry 44
2.B.4 Correlation of Robot Stock and Patents 44
2.B.5 Correlation of AI Patents, AI Firms and AI Job Vacancies 45
2.B.7 Regional Cumulative Exposure to AI and Robotics in 2018 46
2.B.8 Firm Level Employment Effects of AI and Robots by Skill 47
2.B.10 District Level Employment Effects of AI and Robots by Skill . . . 48
2.D.7 Example of a robot patent document 58
2.D.8 Example of an AI patent document 59
2.D.9 Evolution of Patents by Broad Technology Class 60
2.D.11 ALP process based on Lybbert & Zolas (2014) 61

3.1 AI, Robots, and Job Tasks 76
3.2 Technology and Individual Job Tasks 78
3.3 AI and Detailed Job Tasks 81
3.4 Robots and Detailed Job Tasks 82
3.A.1 Cumulative Robot Patents by Industry 97
3.A.2 Evolution of AI and Robot Patents over Time 98
3.A.3 AI, Robots, and Interactive and Manual Tasks 99

4.1 Correlation between digitalisation measures and working conditions 113
4.2 Correlation between digitalisation measures and training participation 114

List of Tables

2.C.1 Plant-level Employment and Wage Effects 49
2.C.2 Plant-level Employment and Wages by Skill 50
2.C.3 Plant-level Employment and Wage Effects in Manufacturing and Services 51
2.C.4 District Employment and Wage Effects 51
2.C.5 District Employment and Wage Effects in Manufacturing and Services 52
2.C.6 District Employment and Wage Effects by Skill Group 53
2.D.1 Top Using Industries of AI and Robotics Patents 54
2.D.2 Industries with Strongest Growth in AI and Robotics Patents . . . 54
2.D.3 Plant Characteristics and Exposure Measures 55
2.D.4 Local Labor Market Characteristics and Exposure Measures . . . 56
2.D.5 Plant-level Robustness Checks 57
2.D.6 District Employment and Wage Effects - No German patents . . . 57

3.1 Balancing test 74
3.2 Technology and Individual Job Tasks 79
3.3 Comparing the Effects across Time 83
3.4 Heterogeneity by Skill 85
3.5 AI, Robots, Employment, and Earnings 90
3.6 AI, Robots and Worker Reallocation 92
3.7 AI, Robots and Reallocation by Task Intensity 94
3.8 Heterogeneity by Skill and Age 95
3.B.1 Descriptives of Task Groups and Detailed Task Shares 100
3.B.2 Heterogeneity by Age 101
3.B.3 Robustness tests 102

4.1 Summary statistics 112
4.2 Digitalisation and Working Conditions 119
4.3 Digitalisation and Training Participation 122
4.4 Digitalisation and Working Conditions - ICT Investments 123
4.5 Digitalisation and Training Participation - ICT Investments 124
4.A.1 Top and Bottom 10 Occupations for Routine Task Intensity 134

4.A.2 Top and Bottom 10 Occupations for Computer Substitution Potential 134
4.A.3 Top and Bottom 10 Occupations for AI Exposure 135
4.A.4 Top and Bottom 10 Occupations for Machine Learning Suitability 135
4.A.5 Occupations by Average Training Participation 136
4.A.6 Digitalisation, Working Conditions and Training - by Age 137
4.A.7 Digitalisation, Working Conditions and Training - by Gender . . . 138
4.A.8 Digitalisation and working conditions - conditional on training . . 138
4.A.9 Digitalisation, Working Conditions and Training - Management Controls 139
4.A.10 Digitalisation, Job Satisfaction and Sick Days 140
4.A.11 Digitalisation, Well-being and Work-life Balance 141
4.A.12 R1: Working Conditions and Training - Employees in minimum two waves 142
4.A.13 R2: Working Conditions and Training - Employees in four waves . 143
4.A.14 R3: Working Conditions and Training - Exposure above median . 144

x

Chapter 1

Introduction

Technological change is one of the main drivers of long-term economic growth, and economists have identified the introduction of new technologies as a key factor for increasing productivity (Romer, 1990; Jones and Liu, 2024). Since the invention and widespread availability of the Internet, rapid advances in digitalisation have increased productivity and enabled new business models, contributing to economic growth. In recent years, artificial intelligence (AI) has continued to push the boundaries of what machines can do, and the question of how this technology affects the economy and labor markets, in particular, is gaining importance (Brynjolfsson et al., 2018; Agrawal et al., 2019). The development of new AI technologies has been rapid, and a particularly striking example is the introduction of ChatGPT in 2022. This new technology based on large language models gained 1 million active users in just 5 days and continues to grow rapidly (Marr, 2023). AI and large language models are now so prevalent that they are considered general-purpose technologies (Eloundou et al., 2023).

As with previous waves of rapid technological change, there is a widespread fear of technological unemployment caused by the automation effects of digitalisation. Large-scale unemployment is predicted when machines become better at performing tasks where humans previously held an advantage, and AI is pushing these boundaries even further (Kessler, 2023). Most of these concerns start with the tasks humans perform in their jobs and the number of tasks AI can (potentially) perform. In labor economics, this is modeled theoretically and has been labeled the task-based approach (Autor et al., 2003; Acemoglu and Autor, 2011). In a production process that uses capital and labor as inputs to produce goods or services, the inputs are divided to perform different sets of tasks. The division of tasks between capital and human labor depends on various factors - the technological feasibility of automating a given task being one of them.

Task-based models are the theoretical background for the three empirical essays in this thesis. In each essay, I investigate different aspects of the labor market impacts of digitalisation. The focus is on artificial intelligence and how its impact compares to the impact of robots, which represent an established automation technology. Robots are a technology that has been heavily deployed since the late 1990s and that primarily automates routine manual tasks in manufacturing (Graetz and Michaels, 2018). Yet, the empirical evidence on the overall employment effects of robots remains mixed. Some studies show that robots increase employment and make adopting firms more productive (Koch et al., 2021). Others find negative employment effects on a regional level (Acemoglu and Restrepo, 2020).

In contrast to robots, AI is a more recent technology that potentially affects different tasks. While robots primarily focus on routine manual tasks, AI technologies can automate and complement human labor in a wide range of tasks. One of these tasks is decision-making, where AI systems analyze huge quantities of information to ultimately guide or automate human decision-making (Agrawal et al., 2019). With the availability of generative AI, it can even perform creative tasks such as generating pictures and videos or composing music. Overall, there are abundant examples that show how AI can automate tasks but also complement human labor and make it more productive. While the tasks performed by robots are relatively clearly defined, it is more difficult to gauge the tasks affected by AI. While there is an automation component, AI also complements human labor in a wide range of tasks and introduces completely new tasks. One example is prompt engineering, a task that did not exist before the introduction of AI chatbots.

The question of which tasks, occupations, and workers are affected by AI and robotics lies at the heart of all three essays in this thesis.

The first essay investigates the aggregate employment and wage effects of AI and robotics in Germany. The second zooms in on the effect of AI and robotics on the task content of occupations and individual worker careers. The third essay investigates the impact of basic and advanced digital technologies on job quality and employer-provided training.

In the second chapter of this thesis, which is joint work with Christina Gathmann, we use patent data to develop new measures for the advancement of AI and robots and study their impact on employment and wages in Germany at the firm and local labor market level. We find that patenting in robots and AI technologies increases over time, with robots taking off in the early 2000s and AI starting to expand around 2015. For German firms, we find that those in industries more exposed to AI experience negative employment effects. In contrast, robot exposure decreases low-skill employment but increases medium- and high-skill employment. AI positively affects wages, while robot exposure is associated with lower wages. Next, we analyze the impacts of AI and robot exposure on local employment and wages using a shift-share design for German districts. At the local level, we find negative employment effects for AI, which are strongest for medium-skilled workers, confirming the hypothesis that AI affects workers higher up on the skill distribution. Robots have a small positive overall effect on local employment, but they also negatively affect the employment of low-skill workers.

Compared to the growing number of studies on the aggregate employment and wage effects of AI and robots, the impact on the actual tasks performed at work and the outcomes of individual workers are relatively less studied. In the third chapter, which is joint work with Christina Gathmann and Erwin Winkler, we contribute to answering this complex question by zooming in on how AI and robots affect the task content of occupations. We use the same patent-based measures of AI and robot exposure as in the previous section and combine them with survey data on tasks performed at work as well as with administrative employment records of workers. We find that AI and robots differ substantially in their impact on the task content of jobs. Robot exposure mainly decreases the share of routine (manual) tasks. AI, in contrast, shifts the task content from non-routine abstract tasks towards routine tasks. This happens within occupations and is strongest for low- and medium-skilled workers in manufacturing. Next, we link our measure to individual-level data from Germany and show how AI and robots affect workers. We find that exposure to AI increases the likelihood of switching jobs, resulting in decreased days employed and a small negative effect on wages. The job changes mainly occur within the same 2-digit industry. Robot exposure, in turn, decreases the likelihood of job switches and makes worker careers more stable.

As shown in the first two essays, AI and robot exposure affect the task content of occupations, individual worker careers, and aggregate employment and wages at the level of firms and local labor markets. Yet, new digital technologies affect not only the number of jobs and the wages paid to workers but also the quality of jobs. Compared to the number of studies focusing on the quantity of jobs, the quality of jobs receives relatively little attention. Yet, it is an increasingly important topic to study as it is directly related to employee well-being, health, and productivity (OECD, 2023).

In the fourth chapter of this thesis, I study the impact of digitalisation on job quality and employer-provided training in Germany. Using novel data that combines an employer-employee survey with administrative records and occupation-level measures for digitalisation, I differentiate between the impact of basic digital technologies, such as computers and computer-controlled machines, and that of advanced digital technologies, such as AI and machine learning. AI exposure is associated with better working conditions, while exposure to basic digital technologies is associated with worse working conditions. The same pattern applies to participation in employer-provided training. Exposure to AI increases the propensity to participate in further training, whereas exposure to basic digital technologies reduces it.

I further show that participating in employer-provided training can mitigate some of the negative effects of basic digital technology exposure and that the negative effects are stronger in firms that invest in digital technologies. This highlights the role of firms in technology adoption decisions and opens up the scope for employee-centric personnel management to counter potential negative effects.

In the following, I will introduce each chapter in more detail.

1.1 Labor Market Effects of AI and Robotics

The second chapter investigates the impact of AI and robot exposure on employment and wages in Germany. This effect is analyzed at two different levels: at the firm level and then at the level of local labor markets.

We develop a new measure for the advancement of AI and robots based on patent data from the European Patent Office. To create this measure, we first perform Natural Language Processing steps on the text of patents to classify them into AI or robot technologies. Next, we use a probabilistic mapping (Lybbert and Zolas, 2014) to map them to industries where they are used. This step allows us to estimate the effects of patenting on technology users and not only on inventors.

Combining the patent-based measures with administrative data on German plants between 1993 and 2021, we investigate how increased exposure to AI and robots affects employment and wages. The data allows us to disentangle further the effects on workers of different skill and age groups.

At the plant level, we find negative employment effects of AI that are mostly driven by medium- and high-skill employment. For robots, we find negative employment effects for low-skilled workers but positive effects for medium- and high-skilled workers. The wage effects of AI are positive for all skill groups, while robot exposure is associated with lower wages.

In the next step, we aggregate the administrative data at the district level and investigate the effects of AI and robot exposure on local labor markets. To do so, we employ a shift-share design that uses the advancement in patenting as a shift in the technology frontier, which is attributed to districts based on their industry-employment structure in the base year 1993 (Bartik, 1993; Autor et al., 2013; Acemoglu and Restrepo, 2020). For robots, we find a positive effect on employment but a small negative effect on wages. AI has negative overall effects on both employment and wages. We next investigate heterogeneous effects by skill level and find that robots negatively affect the employment of low-skilled workers but have positive effects on medium-skilled workers. AI has negative employment effects on both low- and medium-skilled workers.

Our study provides a new way to estimate the AI exposure of industries and local labor markets in Germany, which contributes to the literature on patent-based technology measures (Griliches, 1990; Moser, 2005, 2013; Mann and Püttmann, 2023; Webb, 2020; Autor et al., 2024; Prytkova et al., 2024). Using our measures, we contribute to the recent but growing literature on the labor market impacts of AI. By including robot exposure in our analysis, we can show that there are notable differences in the labor market effects of the two technologies. This highlights that predictions of the automation effects of AI can not be drawn from previous technologies such as robots.

1.2 AI and the Task Content of Occupations

The second essay of this thesis continues to explore the effects of AI and robots on the labor market in a different dimension. While the number of studies on the aggregate economic effects of AI and robots is growing, there is still relatively little evidence on how those changes affect the task content of occupations.

In the task-based model, every occupation is composed of a set of tasks that humans perform and that technology can complement or automate (Autor et al., 2003; Acemoglu and Autor, 2011). However, measuring changes in the task content of occupations is challenging due to data limitations and the inherent flexibility and heterogeneity of jobs. To investigate these changes for Germany, we combine the patent-based AI and robot exposure measures introduced in the previous section with additional data. We use a survey on tasks performed on the job and administrative records on individual worker employment spells.

This unique combination of data allows us to structure our analysis in two steps. First, we investigate how the task content of occupations changes over time depending on the exposure to AI and/or robots. Second, we investigate how worker careers are affected by technology exposure, for example, if higher exposure to AI leads to lower job stability.

We find that AI and robot exposure differ in their impacts on tasks. AI exposure leads to a shift from non-routine abstract tasks to more routine tasks. This is in line with the hypothesis that AI enables 'smarter' machines that can now perform more non-routine tasks, whereas human operators are performing more routine supervision or complementary tasks. For robots, we can confirm the findings of previous studies that they automate manual routine tasks and, therefore, shift the task content of occupations in robot-exposed industries to more non-routine tasks. The task shifts occur mainly within narrowly defined occupations within manufacturing and services and are stronger among low- and medium-skilled workers.

Next, we investigate how AI and robot exposure affect individual worker careers. We find that AI exposure is associated with a higher job-switching probability, leading to fewer days employed and a small negative effect on cumulative earnings over 5 years. Workers who change their jobs tend to do so within the same 2-digit industry as their original job. For robots, in turn, we can confirm a finding of an earlier study (Dauth et al., 2021) that exposure to robots decreases job mobility as workers are less likely to change employers or occupations. Employees in industries that are more exposed to robots are more likely to stay in their jobs and industries.

Overall, we find that industry-level technology exposure influences both the task content of occupations and the mobility behavior of employees. There are notable differences between AI and robots, as they affect different tasks.

1.3 Digital Technologies, Job Quality and Employer-provided Training

In the third essay of this thesis, I analyze the impact of digital technologies on job quality and employer-provided training utilizing a comprehensive set of linked employer-employee survey data coupled with administrative records from Germany and occupational digitalisation measures. Job quality is an increasingly important topic, and digitalisation can have wide-ranging consequences for employees. For example, the introduction of new technologies can lead to stress for employees and decrease their well-being (Tarafdar et al., 2007; Ragu-Nathan et al., 2008; Ayyagari et al., 2011; Gerdiken et al., 2021). At the same time, automation of dangerous tasks can improve job quality (Green, 2012; Gunadi and Ryu, 2021; Gihleb et al., 2022). Therefore, the ex-ante effect of digitalisation on working conditions and job quality is unclear.

I compare the impacts of two different technology classes, basic and advanced digital technologies. Basic technologies refer to computers and computer-controlled machines (Dengler and Matthes, 2018) while advanced technologies cover AI and machine learning (Felten et al., 2018; Brynjolfsson et al., 2018). To estimate the effects of digital technologies on working conditions, participation in employer-provided training, and further outcomes related to subjective well-being, I use models with a rich set of controls on the employer and employee level as well as establishment and year fixed effects to account for unobserved differences across employers and time.

I find differential impacts of digital technologies. Advanced digital technologies, such as AI and machine learning, are generally associated with positive outcomes in job quality. Specifically, workers exposed to these technologies report better working conditions and more opportunities for professional development through employer-provided training. This suggests that advanced technologies may augment human capabilities, enrich job roles, and enhance autonomy at work. In contrast, exposure to basic digital technologies negatively correlates with job quality. Workers highly exposed to these technologies experience worse working conditions and lower training participation. Notably, these adverse effects are more pronounced among older and male workers, indicating a demographic disparity in how digital transformations affect the workforce.

The role of employer-provided training emerges as an element in mediating the impacts of digitalisation. My analysis indicates that participation in training can alleviate some of the negative effects associated with high exposure to basic digital technologies by equipping workers with the necessary skills to adapt to new technologies and changes in job tasks. This enhancement of skills helps in building resilience against technostress and automation anxiety. The findings of this essay highlight the importance of employers investing not only in digital technologies but also in enhancing their training and development programs. This dual strategy is essential to ensure that workers are prepared to meet the demands of increasingly complex job roles and to maintain high job quality in the face of rapid technological changes.

Chapter 2

Labor Market Effects of Artificial Intelligence and Robotics[1]

The Fourth Industrial Revolution has dramatically improved the technical capabilities of artificial intelligence (AI), enabling machines to perform and learn tasks at human-like levels of capability in domains including translation and visual image recognition (Pratt, 2015; Schwab, 2016). Improvements in underlying techniques such as machine- or deep learning open up new possibilities for applications in AI, which may be used in a wide variety of industries (Brynjolfsson et al., 2018). Similarly, robots have been diffusing in the economy, and further advances in AI could act as a catalyst for robots to become smarter, less dependent on human guidance, and, thereby, more efficient. There is widespread belief that AI and AI-enhanced robots will reshape the way we work and live.

Yet, we still have a very limited understanding of how AI impacts the labor market. This paper asks how the evolution of AI and robots has affected employment, skill demand, and wages in Germany. A key challenge in answering this question is how to measure the advancement and diffusion of AI and robotics in the economy.

We use patent data from Europe to capture the evolution of the knowledge frontier over the past three decades. Patents are useful to measure the advances in

[1]This chapter is joint work with Christina Gathmann. We thank Christian Dustmann, Albrecht Glitz, Terry Gregory, Michael Stops, Eduard Storm, and participants at the AI conference of IZA and Institute for the World Economy, DIW, CESifo, DFG Priority Program 'Labor Markets in a Globalized World', EEA, EALE, the ELMI conference on 'Skills for the Future', University of Duisburg-Essen, University of Trier, IZA Summer School and Verein für Socialpolitik for helpful comments and suggestions. We are grateful to Jongoh Kim for excellent research assistance.

emerging technologies and are often used as proxies for innovation.[2] Griliches (1990) and Moser (2005, 2013) provide thorough discussions of the benefits and limitations of using patent data. Patents provide rich information on how and where the knowledge frontier advances in specific technologies. Firms can make use of the shifting technological frontier by adopting the new knowledge in their production processes.

We build our measures using data from the European Patent Office together with text mining and natural language processing to find patents related to AI and robotics. We then link the patents to the industries that can use them by applying a probabilistic concordance scheme developed by Lybbert and Zolas (2014).[3] The new patent-based measures enable us to track the technological frontier of robotics and AI in detailed industries and within industries over time. We use robotics patents both to validate our patent-based approach and to compare the results in the labor market to those of AI.

We then assess the labor demand and wage effects of AI and robotics, combining our patent-based measures with administrative social security records from Germany. Our analysis is performed at the firm level[4] and for the local labor market. The firm level identifies the net effect of AI and robots on adopting and non-adopting firms in exposed industries. The local labor market approach, in turn, quantifies the impact of AI and robot exposure on the local economy, including reallocation and spillover effects. The two levels of analysis rely on different identifying assumptions, which increases the confidence that the estimates we obtain are indeed causal.

We have five main results. First, we find that AI reduces overall employment in exposed industries. Second, we find a small positive wage effect for employed workers. These two results together indicate that AI has so far largely been an instrument of automation with only modest productivity gains. Third, the

[2]Patents are exclusive rights of use for novel solutions to technical problems. In exchange for these exclusive rights, all patent applications are published, revealing technical details of the invention.

[3]Lybbert and Zolas (2014) match keywords from the description of patents to keywords extracted from the definition of industries in SITC and ISIC codes. Then, they construct a probability match of IPC/CPC code classes to industries based on the amount of keyword matches obtained.

[4]To be precise, our data is at the level of plants. We will use 'plant' and 'firm' interchangeably in the following.

results of AI stand in sharp contrast to those of robots. Firms exposed to robots actually experience small positive employment effects together with very small wage reductions. Fourth, AI also reduces employment at the *local* level, suggesting that the displacement effects in exposed industries are not compensated by employment growth in other industries. Moreover, the negative employment effects of AI are visible in manufacturing but also in the service sector.

Finally, we investigate the skill bias of the new technologies. AI replaces workers higher up the skill distribution as employment declines, esp. for medium-skilled workers. Firms also reduce their demand for high-skilled workers in industries exposed to AI, but they get absorbed by the local economy. Robots, in contrast, replace low-skilled workers but increase the demand for medium- and high-skilled employees. These results indicate that robots exhibit a clear skill bias, while AI does not seem to decrease employment in the middle of the skill distribution.

We contribute to the literature in at least three ways. First, we provide new measures of how new digital technologies like robotics and AI have affected workplaces. Many studies have used broad measures such as firms' R&D expenditure or investments in information and communication technologies (ICT) (Bloom et al., 2014; Bresnahan et al., 2002; Caroli and van Reenen, 2001). Yet, such broad measures make tracking of specific digital technologies like AI inherently difficult. Other studies use direct measures on specific technologies such as the number of robots installed in broad industries (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021) or by firms (Koch et al., 2021; Acemoglu et al., 2020; Dixon et al., 2021; Bonfiglioli et al., 2020). The drawback is that these measures are available for a limited set of technologies and, in the case of robots, only for a small number of industries. Our measures allow characterizing the evolution of two path-breaking technologies for a broad set of industries over three decades.

A third approach uses occupation-level measures constructed from information on tasks performed on the job. Earlier research relied on experts (Frey and Osborne, 2017) or crowd workers (Brynjolfsson et al., 2018) to assess the potential of digital technologies for replacing labor. Very recently, authors have combined patent data with information on tasks performed on the job to quantify the automation potential of digital technologies (Felten et al., 2019; Webb, 2020). These measures provide a snapshot of how automation could replace tasks and possibly occupations in the future. Yet, because these measures are cross-sectional, they can tell us little about the dynamics of the digital transformation. Most importantly, these measures are silent about the potential of digital technologies to enhance productivity or create new tasks and occupations.

There are advantages and disadvantages to our patent-based measures of technological advances compared to investments in ICT capital, robot installations, the routine task share, or the automation potential of occupations. Our measure is broad and likely to contain measurement error in classifying patent texts. The probabilistic mapping of patents to industries might introduce additional imprecision [5]. We also need to assume that patents are useful when implemented in the production process. All these should bias us against finding an impact on the labor market. An advantage of our approach is that we impose no ex-ante assumptions on whether these technological advances reduce or increase labor demand. Moreover, patent-based measures closely track the actual technology frontier, which varies across detailed industries depending on the production technology and evolves dynamically over time. Finally, we can validate our measures by comparing our results for robot exposure to the large literature using robot installations at the industry level as an exposure measure instead.

Closely related to us are studies based on patents, which have long been used in the innovation literature to proxy innovation (Griliches, 1990) and technology diffusion (Jaffe et al., 1993). Patent meta-data, such as citation counts or the location and identity of inventors, has been used frequently (Hall et al., 2001; Acemoglu et al., 2014; Bell et al., 2018) in innovation research. More recently, researchers have gone beyond the sheer number of patents and analyzed the actual text of patent documents (see Bessen and Hunt, 2007, for an early example). Often, these focus on the industry that produces the knowledge rather than the industry

[5] Mann and Püttmann (2023) use a similar process of mapping patents to industries of use with a concordance scheme developed by Silverman (2002).

that implements that knowledge in its production process (Dechezleprêtre et al., 2020; Montobbio et al., 2022). Most closely related are studies creating patent-based measures of automation potentials (Mann and Püttmann, 2023) or digital technologies more broadly (Prytkova et al., 2024).

Our measures characterize the evolution of two major technologies, AI and robotics, over time. We make no assumption on how these technologies affect labor: they may replace some workers but also raise the productivity of other workers or even result in the reorganization of work and the emergence of new jobs. Hence, our evidence is not limited to identifying the automation effect of digital technologies. In addition, our measures go beyond the actual usage of new technologies in industries but capture the evolving technological frontier. Finally, our measures reflect the diffusion of digital technologies in Europe, which has experienced a different dynamic than the United States. Europe, particularly France and Germany, are leaders in the adoption of robotics technology; at the same time, they lag behind the United States and China in the development and use of AI technologies.

Our second contribution is to the literature on the effects of digital technologies on the labor market. Most studies have focused on the diffusion of robots in the manufacturing sector. The results differ widely, ranging from negative (Acemoglu and Restrepo, 2020), close to zero (Graetz and Michaels, 2018), or even positive employment effects (Dauth et al., 2021). Firm-level evidence, in contrast, indicates that adopters of robotics technology are not only more productive but also grow after adoption and outperform their competitors within the same industry (Acemoglu et al., 2020; Alderucci et al., 2021; Benmelech and Zator, 2022; Koch et al., 2021). The empirical evidence for AI technologies is scarce and shows few links between AI technology measures, employment, or wages by industry or occupation (Acemoglu et al., 2022; Bonfiglioli et al., 2023; Albanesi et al., 2023).

Third, we complement previous studies focusing on the effects of technologies such as AI on tasks in occupations (Brynjolfsson et al., 2018; Felten et al., 2018; Webb, 2020; Gregory et al., 2019). Recently, Webb (2020) proposed new measures of time-invariant exposure of occupations to three different technologies: information technology, robots, and AI. However, the measure is based on US patent and occupational data and, therefore, is not easily transferable to European data. Also, it is a static measure that does not provide time variation. Similarly, Autor et al. (2024) generate measures of the evolution of new tasks from O*Net to track their impact on workers' careers. As for Webb, the proxies for technological change cover the U.S. and vary at the occupational level, which are not easily transferable to our context.

The paper proceeds as follows. The next section presents our patent-based measures and explains how we identify AI and robotics patents and link them to the industries that can use them. Section 2.2 provides some descriptive evidence on our patent measures and compares them to existing proxy variables, such as data on robot installation and AI-related job vacancies. In Section 2.3, we introduce our administrative labor market data from Germany. In section 2.4, we discuss the empirical strategy for our estimations at the firm level and present results on the employment and wage effects of AI and robots. In Section 2.5, we investigate the effects of AI and robots at the local labor market level. We present robustness checks in Section 2.6 and, finally, conclude in Section 2.7.

2.1 Patent-based Measures of AI and Robotics for Europe

We use patents to measure the technological advances in AI and robotics. Patents are major innovations in a given technological field containing detailed information on the additional knowledge or process. Our data covers the universe of patents filed with the European Patent Office (EPO) between 1990 and 2018. The approach proceeds in three steps. First, we prepare the data for applying text analysis to the title and abstract describing each patent. In the second step, we use natural language processing techniques to identify patents in robotics and AI technologies. In the final step, we match the identified patents to the industries most likely to use them in their production process. We now describe each step; more detail can be found in the data appendix.

2.1.1 European Patent Data

We use data on all patents granted by the European Patent Office (EPO) between 1990 and 2018, which we extract from the World Patent Statistical Database (PATSTAT). Important innovations are patented in all major patent offices. Any invention a firm wants to have protected in the European market will be patented at the EPO even if the innovation occurred abroad. The patent documents include the title and abstract of each patent, the name, company, and location of the inventor, the dates of application, and the grant of the patent. The technical content of a patent is categorized by its IPC or, more recently, CPC codes, which are very detailed classifications with several thousand entries. These codes are assigned by highly specialized experts, the patent examiners.

To identify patents covering innovations in the field of AI or robotics, we analyze the titles and abstract of a patent.[6] Though each patent document includes a title, abstracts are missing for about 30% of the patent grants. In that case, we use the IPC/CPC code from the narrow or extended patent family to describe the technical content of a patent. Using this procedure, we can impute two-thirds of the missing abstracts.

We then convert all patent abstracts and titles to text corpora using the following pre-processing steps: we convert all text to lowercase, then remove numbers, special characters, punctuation, and stop words. Next, we strip the text of any blanks and white spaces. Finally, we extract word stems and divide the text into *tokens*.

2.1.2 Identifying Patents in Robotics and AI

We use a combination of patent classification codes (IPC/CPC) and keyword searches of the patent title and abstract to identify patents related to robotics and AI. For robots, the technology is clearly defined. The ISO 8373 definition defines a robot as an "actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended

[6] Following the patent literature, we do not use the full text of the patent description or claims. These texts are written by patent lawyers in generic language to increase the protective scope of a patent.

tasks". Robots are further grouped into industrial or service robots based on their intended application. We identify robotics patents if they belong to the CPC code B25J9: "Programme-controlled manipulators"; or if they match a keyword search conducted over the titles and abstracts of all patents.

Unlike robotics, AI is a very broad concept that spans multiple technologies. We identify AI patents in several steps. First, we use all IPC/CPC codes that are directly connected to a specific AI technology or sub-field like machine learning, neural networks, or fuzzy logic using a list of AI-specific IPC/CPC codes from the World Intellectual Property Organization (2019). An example is code G06N7/046 'Computer systems based on specific mathematical models - implementation by means of a neural network'. However, there are only a few IPC/CPC codes for software or algorithms, and most AI-related inventions are not identified by these codes. Prominent examples are speech and image recognition, two of the most important applications of AI. Many AI innovations are instead embedded in patent applications in other technology fields. One such embedded innovation is level 4 and 5 autonomous driving, which relies heavily on AI-driven image recognition. As a second step, we conduct a keyword search over the titles and abstracts of all remaining patents based on a keyword list compiled from the World Intellectual Property Organization (2019) and Baruffaldi et al. (2020). Examples of keywords include machine learning, natural language processing, fuzzy logic, or decision tree.[7]

Appendix figures 2.D.7 and 2.D.8 show patent applications with highlighted keywords identifying them as robot and AI patents, respectively. The examples show that patent titles often include specific terms like neural networks, while the abstract contains more general technological concepts such as artificial intelligence or machine learning.

Overall, we obtain around 11,000 unique robotics patents and 7,000 AI-related patents. Panel (A) of Figure 2.B.1 shows the evolution of robotics patent grants

[7]Our keyword list is shorter than the list used in World Intellectual Property Organization (2019) in order to reduce false positives. Their keyword list includes keywords like network, algorithm, logic, and boost, which can potentially be found in many patents unrelated to AI technologies.

and applications between 1990 and 2018. Robot patents show a first peak in the mid-1990s and then again in the late 2000s. Patent applications for robotics continue to grow throughout the whole time period. Panel (B) in Figure 2.B.1 shows that AI patent grants started to emerge in the mid-1990s but remained low until 2015. Patent applications for AI technologies shoot up after 2015, especially in 2017 and 2018.

Appendix figure 2.D.9 provides the first descriptive evidence in which sectors of the economy innovations in AI and robotics occur. We use a mapping of IPC codes to thirty-five technology classes (following Schmoch, 2008) and aggregate them to five broad technology classes: Electrical engineering, mechanical engineering, instruments (e.g., optical instruments, control technology, and medical technology), chemistry (e.g., pharmaceuticals, biotechnology, food, and materials) and other (e.g., many consumption goods like furniture, but also civil engineering).

Robotics technology is heavily concentrated in mechanical engineering (see Panel (A)). In recent years, robotics have become more prevalent in instruments and others, which points to new applications beyond mechanical engineering and industrial robots. Panel (B) of Appendix figure 2.D.9 shows that AI technologies are most prominent in electrical engineering but have recently become more important in instruments.

2.1.3 Robotics and AI Technologies at the Industry Level

As our ultimate goal is to understand how the diffusion of AI and robotics shifts the demand for labor, we need to match the patents to the industries where the technology is used – not where the patent has been developed (see Mann and Püttmann, 2023). Linking patents to the industries that use them in their production process is inherently difficult. Measuring the usage of a specific patent within an industry requires identifying the specific product or service in which the patent is embedded. Such information is not available. Instead, we treat patents as proxies of the evolving knowledge frontier in a given technology, which improves existing or opens up entirely new possibilities in the production of goods and services.

We use a concordance scheme between CPC codes and 4-digit ISIC industry codes developed by Lybbert and Zolas (2014) and updated by Goldschlag et al. (2019) [8]. A key advantage over older concordance schemes developed by Kortum and Putnam (1997) or Silverman (2002) is that it can better capture recent developments in AI and robotics.

Appendix figure 2.D.11 illustrates the connection between technological knowledge embedded in a patent and industries that make use of this knowledge. Starting from a description of the activities in an industry given by the official classification, a keyword search matches industries to patents if the industry's activities share one or more keywords with the patent description. The result is a list of patents with their IPC/CPC codes linked to industries producing with the knowledge embedded in the patent. The match frequency is used to calculate a probabilistic weight for each industry. The weight is based on Bayes' rule, taking into account the number of possible codes and how often a code is matched to an industry. Patents are then assigned proportionally to industries of use [9].

Appendix table 2.D.1 shows the 4-digit industries with the highest number of AI patents (in the top panel). AI-related patents are heavily used in the manufacturing of ICT, but also in machinery, and measuring equipment. Interestingly, AI patents are also important in the music and film industry (see ISIC codes 5912 and 5920 in appendix table 2.D.1). The table further reports the share of patent grants in AI for each industry. The average share of AI patents across all industries is 0.21%, which indicates that AI has so far contributed only a small share of the overall patents used in an industry. Yet, most industries with a high number of patents also have a high share of AI patents. In contrast, among the industries without any AI patents are many services like real estate, care, tourism, early childhood education, and farming. The bottom panel of appendix table 2.D.1 shows the

[8] In contrast to concordance schemes that focus on the industry of innovation (Dorner and Harhoff, 2018), our walkover identifies the industries in which the new technological opportunities are potentially used by firms in production.

[9] The probability weight is also higher for codes strongly linked to particular industries. Matches with high specificity in a certain technology class likely indicate particularly strong linkages to certain industries compared to broad innovations that match many different industries.

industries with the highest number of robotics patents. Not surprisingly, robotic patents are mostly used in manufacturing – both in absolute number and relative to the average patent use of 0.32% across all industries.

2.2 Technology Exposure and Technology Use

2.2.1 Defining the Exposure Measure

To study the labor market consequences of the new technologies, we aggregate the patents into an exposure measure that tells us how much detailed industries are exposed to new developments in AI and robotics over time. In the first step, we follow the approach of Mann and Püttmann (2023) and log-transform industry-level patents in each technology to account for the large differences in patenting activity across industries. We show below that alternative measures using the raw patent count or an inverse hyperbolic sine transformation yield very similar results. The second step is to account for the fact that yearly variations in patent grants will not reflect the cumulative nature of knowledge creation. Therefore, we calculate cumulative measures summing patents for four periods: 1990-1998, 1990-2004, 1990-2011, and 1990-2018. The resulting measure is thus defined as follows:

$$AI_{i,t} = \sum_{s \in t} Log(1 + AIPatents_{i,s}) \tag{2.1}$$

$$Rob_{i,t} = \sum_{s \in t} Log(1 + RobPatents_{i,s}) \tag{2.2}$$

where i is the industry applying the patents and t the sub-periods 1990-1998, 1990-2004, 1990-2011, and 1990-2018. The measures in equation (2.1) take on four values for each detailed industry.

Figures 2.B.2 and 2.B.3 show the distribution of the cumulative patent measure over 2-digit industries. The figures show the distribution in the last period, hence depicting the sum of log patents between 1990 and 2018. AI patents are concentrated in the manufacturing of computers and electrical equipment, followed by various manufacturing industries. Robots are concentrated in manufacturing, especially in electronic products and machinery and equipment.

Our patent measures describe the knowledge frontier in robotics and AI. Yet, our patent-based measures should not only capture exposure to technological advances; but also correlate with the actual adoption and diffusion of the technology by firms in the exposed industry. We next demonstrate that our measures correlate positively with various proxies for using robots and AI.

2.2.2 Robotics Patents and Robot Installations

Advances in robotics measured by our patent data should increase the likelihood that firms purchase and install industrial robots in their production. To investigate this, we use data on robot installations from the International Federation of Robotics (IFR) (International Federation of Robotics, 2020). The IFR data track the installation and stock of robots in around fifty countries. The dataset contains the number of robot installations per year in broad industries, most of them in manufacturing. We use the information on robots installed in Europe to ensure we have the same geographic coverage as the patent data from the European Patent Office. Unfortunately, the IFR data only has information on thirteen industries in manufacturing and six other broad sectors.[10] We aggregate our patent measures, which are available at the 4-digit level, to the 2-digit level and match them to the IFR classification. We compare the stock of robots in 2018 to the sum of robot patents until 2018 as defined in equation (2), both measured in logs. Figure 2.B.4 shows a strong positive correlation between our patent measure and robot installations. Based on the industry classification used by the IFR, there are also industries where robot patents could potentially be applied according to our measure. Still, no installations have been recorded in some industries so far. This highlights the fact that we are approximating the technological frontier with our measures.

[10]The manufacturing industries are food and beverages; textiles including apparel; wood and furniture; paper and printing; plastics and chemicals; minerals; basic metals; metal products; industrial machinery; electronics; automotive; shipbuilding and aerospace; and miscellaneous manufacturing including production of jewelry and toys. The other broad sectors are agriculture, forestry and fishing, mining, utilities, construction, education, research and development, and services. About 30 percent of robots are not classified into one of the nineteen IFR industries though this share declines over time. Following Acemoglu and Restrepo (2020), we allocate unclassified robots to industries in the same proportions as in the classified data.

2.2.3 AI Patents, AI Firm Share and AI Job Vacancies

Obtaining a proxy for whether a firm uses or has adopted AI is much more difficult. Our first measure uses the number of online job ads that require AI skills to proxy for the AI activities in firms (see also Acemoglu et al., 2022). Firms that (want to) adopt AI are likely to require some job profiles like programmers, data scientists, or engineers who are familiar with AI tools. Firms in industries exposed to more advances in AI might, therefore, post more vacancies requiring AI skills if they lack the competencies in-house.

Our data for online job vacancies in Germany come from Lightcast and cover 2021. We identify job ads that require at least one AI skill using the keyword list from Alekseeva et al. (2021), including search terms such as neural networks, deep learning, NLP, or machine vision. As there is no reliable industry classification in the job ads, we use the detailed occupation and the occupation-industry distribution for Germany to map the job ads to our patent measure.

Panel A of figure 2.B.5 shows a positive correlation between the number of job ads with at least one AI skill and the number of AI patents granted in 2-digit industries for Germany. Hence, patents encourage investments in tangible and intangible capital embodying AI technology and raise the demand for workers who can use and apply AI technology.

Yet, AI skills in job ads might not capture the actual AI activities of firms very well either because firms that adopt AI have the competencies in-house (and hence, do not advertise jobs requiring AI skills); or because they can adopt AI without hiring additional staff with specialized AI skills. As an alternative proxy, we deduce the AI activities of all companies in Germany from their websites. The data come from ISTARI.AI for 2022, a German startup that builds company-level indicators based on large-scale scraping of company websites combined with a proprietary AI algorithm. One indicator is the firm's AI knowledge, which is calculated either based on direct evidence like actual AI used on the website (e.g., a chatbot for customer relations); or more indirectly based on AI activities or investments mentioned on the company website. We calculate the share of firms with AI knowledge among all firms in a given industry at 3-digit ISIC level and correlate it with our patent measure. Panel B of figure 2.B.5 again shows a positive correlation between the share of firms with AI knowledge and the cumulative number of AI patents in an industry.[11]

2.3 Administrative Plant-level Data

We use administrative data on plants to investigate the labor market consequences of AI technologies and robotics. The data come from the German Establishment History Panel (BHP), a 50% random sample of all plants with at least one employee covered by the social security system in Germany (see Ganzer et al., 2020, for more details). The social security data cover around 80% of the German labor force, excluding civil servants, military personnel, and the self-employed. Our plant sample spans the years from 1993 to 2021. We match our measures of AI and robot technologies, which vary by detailed industry and year, to the plant data by the detailed (3-digit) industry.[12]

We observe the number of employees at each plant, which we can use to analyze overall employment effects when the industry becomes exposed to AI and robot technologies. The data include detailed information on the socio-economic composition of the workforce by age, gender and skill in each plant. We distinguish three skill groups - low, medium, and high skilled - based on the highest qualification obtained. High-skilled workers are workers who have graduated from a college or university. Medium-skilled workers have completed a vocational training program or obtained the university entrance certificate after high school (*Abitur*). Low-skilled workers have lower qualifications or no qualifications at all. In the raw data, the education variable is missing for about 9% to 37% of the observations depending on the year. We impute missing education information following Fitzenberger et al.

[11]A number of industries have a high firm share of AI knowledge but zero AI patents. These can mainly be attributed to service industries such as business and IT consulting, where patenting AI is unlikely but that are actively adopting AI tools. Nevertheless, the positive correlation shows that industries with a high number of patents are also those where a lot of AI-related economic activity happens.

[12]We use a crosswalk provided by EU RAMON to convert the ISIC rev. 4 classification of our patent measures to the European NACE rev. 2 classification, which is equivalent to the German industry classification (WZ08) at the 3-digit level.

(2005), which reduces missings to less than 1%. We further distinguish three broad age groups (20-34, 35-49, and 50-64). We also expect that digital technologies affect some occupational groups more than others. To analyze who might benefit and who might lose, we use the information on the occupational structure in the plants (e.g., the share of simple manual jobs, clerks, technicians, skilled manual labor, engineers, professionals, and managers) and on the type of employment contracts used (e.g., fixed-term contract, temporary worker).

Finally, we also observe plant-level wages. As is common in social security records, wages are right-censored at the highest level of earnings subject to social security contributions. Wages are imputed based on the imputation procedure of Gartner (2005). We observe the wage distribution in each plant, which is characterized by the 25th, 50th, and 75th percentile wage. The wage information is available for full-time workers, for the three skill groups, and by gender. Appendix table 2.D.3 reports summary statistics at the plant level.

2.4 AI and Robots: Plant-level Evidence

2.4.1 Estimation Approach at the Plant Level

We start out by analyzing the direct impact of technological innovations in AI and robotics on employment and wages at the plant level. After merging the exposure measure at the industry x period level from equation (2.1) to our plant-level data, we then estimate variants of the following model:

$$Y_{fit} = \beta_{AI} Pat^{AI}_{i,t-1} + \beta_{Rob} Pat^{Rob}_{i,t-1} + \gamma' X_{it} + \theta_f + \delta_t + \epsilon_{fit} \tag{2.3}$$

where f denotes the plant, i the industry, and t the period (1999-2004, 2005-2010, 2011-2016 and 2017-2021).

The key independent variables are our two measures of cumulative knowledge in AI and robotics technology in period t in industry i ($Pat^{Rob}_{i,t}$ and $Pat^{AI}_{i,t}$). As the diffusion and adoption of technologies encoded in patents only occur with a time lag, we allow patents granted between 1990 and 1998 to affect employment and wages in the period 1999-2004, while patents from 1990 to 2004 may influence labor market outcomes from 2005-2010, etc.

The main outcome variables Y_{fit} are plant-level employment (defined as *log employment*) and wages (defined as *log wages*) overall and by skill group. Our specification includes period fixed effects (δ_t) to control for aggregate changes through the business cycle or other aggregate shifts in employment or wages. We further include firm fixed effects (θ_f) to control for differences in production, pay premiums, or management practices that affect wage or employment growth. We also adjust for firm size differences by controlling for firm employment at the start of each period. To control for other demand side shocks through trade and other investments, we further control for ICT investment and net exports at the industry level. All regressions are weighted by the average employment in the plant over the sample period. We cluster standard errors at the industry x period level.

The coefficients of interest β_{AI} and β_{Rob} reflect how changes in AI or robotics knowledge shift plant-level employment and wages in the industries most exposed to the new technology. It is important to note that the coefficients β_{AI} and β_{Rob} combine the direct effect on plants adopting the specific technology and the indirect effect on non-adopting competitors. Below, we investigate potential reallocation effects through shifts across industries within the same local labor market.

To identify the causal effects of AI and robotics technologies, we require our technology measures to be exogenous to employment changes conditional on our control variables. Demand-side shocks that affect employment and correlate with our technology measures can lead to endogeneity. Therefore, in the estimation, we control for industry-level shocks through trade and ICT investments. Another concern is reverse causality, as firms might adjust their R&D activities in response to changes in wages or shocks to product demand, for instance. Our estimation controls for firm fixed effects to adjust for permanent differences in the innovation potential of firms.

Finally, we assign the patent measures to the industries that might use the innovation, not the industry that produced the patent. Yet, some patents are produced and used in the same firm or industry, and the production of innovation might be influenced by past employment, for instance. Below, we show that excluding all German patents from our technology measures yields qualitatively similar results.

2.4.2 Employment and Wage Effects at the Plant Level

We start out by estimating the effect of exposure to AI and robots on average plant-level employment and wages. Our independent variables of technology exposure are defined at the industry level according to equation (2.1). The dependent variables are mean employment and wages for each period, measured at the establishment level. It is important to stress that we estimate net effects that include both firms that actively adopt AI or robot technologies and firms that do not. Hence, our estimated effects include direct effects of technology adoption as well as spillover effects to competitors or suppliers within the same industry.

Table 2.C.1 shows the impact of AI and robots on employment (columns (1)-(3)) and wages (columns (4)-(6)) based on estimating equation (2.3). We first show the coefficients for each technology in isolation, and then when we control for both technologies jointly. Establishments in industries with a high exposure to AI have lower employment, while exposure to robots actually increases employment. Interestingly, these results emerge only when we control for both technologies in the estimation, as the exposure measures are positively correlated. The AI estimate of -0.005 implies that a standard deviation increase in AI exposure would lead to a decrease in employment of about 1.7%. The magnitude of the robot effect is smaller as a standard deviation increase in robot exposure would increase employment by about 1.2%.

Turning to wages, we find that AI exposure is related to wage growth (see column (6)). The positive wage effect might be either the consequence of changes in the composition of the workforce (induced by the negative employment effect) or could indicate an increase in worker productivity.[13] For robots, we find a small negative wage effect once we control for AI exposure (see column (6)), which is likely to be explained by compositional changes.

[13] As we do not have individual worker-level data, we cannot estimate wage effects holding the workforce composition constant to distinguish between the two channels.

To better understand in which parts of the economy the two technologies shift employment and wages, we next estimate separate effects for manufacturing and services. Table 2.C.3 shows that AI exposure is associated with employment declines in both manufacturing and services, especially once we condition on robot exposure. However, these effects are not statistically significant at the 10% level. For robots, we actually find positive employment effects in firms in the manufacturing and service sectors. The positive wage effects we saw for AI are driven by plants in the manufacturing sector (see column (3)), while for robots, positive wage effects are observed in the service sector.

2.4.3 Skill Bias of AI and Robots

Technological change is rarely skill-neutral. Recent technological advances like the diffusion of computers have been skill-biased, while others, like the replacement of routine tasks, have been polarizing employment at the expense of medium-skilled workers. How do robots and AI influence the demand for different skill groups? To investigate this, we use the number of low-, medium-, and high-skilled workers in each plant as outcomes.

Figure 2.B.8 plots the results of estimating equation (2.3) controlling for each technology separately (Panel (a)) and jointly (Panel (b)). The separate estimation in Panel (a) indicates that both AI and robots reduce employment for low-skilled workers. However, when accounting for their positive correlation across industries, a different picture emerges: AI reduces the employment of medium- and high-skilled workers, while robots actually increase the demand in both skill groups (Panel (b)). Hence, robots are a skill-biased technology that increases the demand for medium- and high-skilled workers. AI, in turn, exhibits no such skill bias as the demand for skilled workers actually declines.

Table 2.C.2 displays the results for employment and wage effects separately for each skill group. There are negative effects on wages for each skill group, indicating that the skill premium remains unaffected by the diffusion of robots. In contrast, wages in plants exposed to AI actually increase for all skill groups.

2.5 AI and Robotics Technologies: Effects on Local Labor Markets

2.5.1 Estimation Approach at the Local Labor Market

Our evidence so far focuses on the net effect of exposure to technological advances in AI and robots on adopters and non-adopters operating in the same detailed industry. Yet, the adoption of new technologies might not only shift business from non-adopters to adopting firms but also shift jobs between industries. AI might encourage firms to in- or outsource certain activities to other companies, for instance. Adopting robots that automate certain activities in firms might free up labor that can move to the service industry (Dauth et al., 2021; Gregory et al., 2019). Depending on the labor intensity of the sector that absorbs workers, total employment might go up or down in the local labor market.

To investigate the potential spillover effects of new technologies, we turn to an analysis at the local labor market level. To that end, we aggregate the plant-level data to the district level (there are 400 districts (*Kreise*) in Germany). Appendix table 2.D.4 presents summary statistics at the local labor market level. For the estimation at the local labor market level, we rely on a shift-share design (Bartik, 1993). Shift-share designs have become popular for studying the impact of trade and technology shocks on local labor markets. In our context, the 'shift' variables are the evolution of AI and robotics technologies as defined in equation (2.1). The 'share' variable proxies for how much a local labor market is possibly affected by the new technologies. We thus characterize each local labor market by its industry structure in the base year. We chose 1993 as our base year as this is the first year when reliable labor market data is available for East Germany.

The local exposure to the technological innovations in robots or AI is then defined as the interaction between initial employment shares in industry i and region r ('shares') and the evolution in AI and robotics technologies in industry i over time t ('shift'):

$$Exposure^c_{r,t} = \sum_{i=1}^{I} \left(\frac{Emp^{1993}_{i,r}}{Emp^{1993}_{r}} \right) * Pat^c_{i,t} \tag{2.4}$$

where r and t indicate the district and time period. Our measures vary both across local labor markets ('district') as well as within districts over time, as new patents are granted in some industries but not others.

Figure 2.B.7 shows the geographic variation in exposure to robotics and AI patents where exposure is constructed as the combination of initial industry shares and the overall growth in patent grants between 1990 and 2018. Most notably, there is a marked difference between East and West Germany as districts in West Germany are much more likely to be exposed to both AI and robotics than districts in East Germany. More districts are exposed to robot technology than AI, which is to be expected as robots have been used much longer than AI technologies.
Exploiting the panel dimension of our data, we then estimate models of the following form:

$$\Delta Y_{r,t} = \beta Exposure_{r,t} + \gamma_1 \Delta Trade_{r,t} + \gamma_2 \Delta ICT_{r,t} + \delta' X_{r,t} + \theta_I + \alpha_r + e_{r,t} \quad (2.5)$$

Here, $\Delta Y_{r,t}$ are changes in employment and wages in each sub-period. Hence, for the first sub-period, for instance, the dependent variables are changes in employment or wages between 1993 and 1998. As before, our main parameter of interest is β, which captures the impact of exposure to AI and robotics on the local labor market. α_r denotes district fixed effects, which control for a district-specific linear trend in employment or wages. All other variables are measured as before. Including region fixed effects implies that the coefficient on the exposure measure (β) in equation 2.5 is identified from shifts in exposure to the two technologies within a district while controlling for overall employment trends in the region. Standard errors are clustered at the district level. For the shift-share design to be valid, either the employment shares or the shift (here, the growth in patents) must be exogenous (Goldsmith-Pinkham et al., 2018; Borusyak et al., 2021). It is important to stress that, in our setting, the growth in knowledge as codified in patents is measured at the European level. Hence, we consider how AI patents produced and patented in e.g. Finland impact local labor markets in Germany. In addition, we estimate the effect for firms *using* patents in the production of goods and services, not for firms producing the patents. It is highly unlikely that the employment conditions and wage levels of firms using the knowledge codified in a patent have an impact on the likelihood or timing of patenting an invention in AI or robotics technology. Both conditions suggest it is reasonable to assume that the shift variable is exogenous to local labor market conditions of using firms. We show below that excluding German patents, which eliminates most links between the production and use of patents, does not affect our results.

A remaining concern of our estimation approach is that there could be differential labor market shocks in regions with industries that are exposed to greater advances in robotics and AI than in other regions. A possible concern is that industry-specific demand shocks might lead to higher usage of AI and robotics in some industries than others. A carmaker exposed to smart driving technology might implement electric vehicles faster if there is a negative shock to the production of fuel cars or some problem in the supply of parts, for instance. To mitigate that concern, we control for trade flows and investments in ICT in our estimation. In addition, we also control for district-specific trends in equation (2.5). This allows capturing any differential trajectories on the labor demand or supply side.

2.5.2 Local Employment and Wages

We estimate equation (2.5), where our dependent variables are changes in employment or wages between the first and the last year of each sub-period. The key independent variables are local exposure to AI and robot technologies as defined by equation (2.4). In all specifications, we control for district characteristics such as ICT investment and net exports and demographic characteristics such as initial employment share by gender, age, or skill. We further control for broad (1-digit) industry employment shares and add district and time (period) fixed effects.

Table 2.C.4 shows the impact of AI and robots for employment (columns (1)-(3)) and wage changes (columns (4)-(6)) in the local economy. As before, we first estimate the effects separately for each technology. The third specification (in

column (3) for employment and column (6) for wages) then shows the impact of AI on the labor market conditional on robot exposure.

AI exposure has reduced employment growth in the local labor market. That implies that the negative employment effects we saw in exposed industries are not compensated by workers shifting to other, more labor-intensive sectors. Based on the specification in column (3), a one standard deviation change in local exposure to AI decreases local employment by around 3 percentage points. Not only does employment decline, but we also observe a small negative wage effect that amounts to around 1.3%, as shown in column (6). Robots, in turn, reduce employment growth in the local labor market, though the effect does not reach statistical significance. Interestingly, conditional on AI exposure, robots lead to local employment growth. The effect amounts to a 1.5 percentage point increase based on a standard deviation change in robot exposure.

An example of a local economy that heavily employs robotics technology and is also very active in the use and diffusion of AI technologies in production processes is the automotive industry. There, robots have been heavily used in the actual production of vehicles, while AI technologies play an important role in the development of smart and self-driving vehicles. We could have regional economies with a weak industrial base but a strong, prosperous service sector. As robots are mostly used in manufacturing, these regions could be little exposed to robotics technology but are at the forefront of using AI technologies. The correlation between the exposure measures in AI and robotics is only around 0.54; as such, we have a lot of independent variation in each local exposure measure.

2.5.3 Manufacturing versus Services

Are the labor market effects stronger in manufacturing or the service sector? While robots are more likely to affect employment in the manufacturing sector directly, spillovers to non-manufacturing employment are expected. While robots are not used intensively in the service sector, indirect effects on service employment and wages can be caused by sectoral mobility, sector-specific job creation, or destruction by firms. For example, firms could offer services that complement robot adoption in manufacturing. In contrast, AI technologies might have diffused into both sectors though the direction of their effect is a-priori unclear. The impact in each sector depends on at least three factors: how many tasks in each sector are susceptible to automation through AI technologies; how strong the offsetting forces of increased productivity and creation of new tasks are; and how attractive the adoption of AI technologies is in each sector, which depends, among others, on the price of labor.

To investigate this empirically, we re-estimate equation 2.4 where the dependent variables are now employment or wage changes in manufacturing and services. Table 2.C.5 shows in the top panel the effects on employment and in the bottom panel the effects on wages.

Both AI and robots replace labor in the manufacturing sector (see columns (1) and (2), Panel A of table 2.C.5), reflecting their substantial automation potential. Robot exposure decreases local employment by 3.4 percentage points based on a standard deviation change in exposure. AI exposure reduces local employment in manufacturing by around 4.4 percentage points. Once we condition on robot exposure, the effect even increases slightly to about 5 points. The advancement of both technologies is, therefore, likely to hit areas with a strong industrial base especially hard.

Columns (4)-(6) also indicate a negative, albeit smaller, effect of AI on the service sector, while robots have little effect. Hence, both robots and AI seem to have a stronger effect in the manufacturing sector. Do these results also hold for wages? The bottom panel of table 2.C.5 shows indeed negative effects on wages in manufacturing, while there is little effect in the service sector.

2.5.4 Skill Bias of AI and Robots at the Local Level

We saw that industries exposed to robots employ more skilled workers, while industries exposed to AI demand less skilled workers. Do these effects also emerge at the local level when individuals can reallocate to other industries? We again use our panel specification from equation (2.5) to estimate the employment and wage effects separately by skill groups.

Table 2.C.6 shows that AI reduces employment growth mostly for medium-skilled workers. This is illustrated in figure 2.B.10, which plots the impact of a one standard deviation change in exposure. Panel (a) shows the effect if we control for each technology separately, while Panel (b) shows their impact conditional on the other technology. Panel (a) shows that AI exposure leads to a decrease in medium-skill employment of 3.8 percentage points.

The negative employment effect for high-skilled workers observed at the plant level in exposed industries vanishes conditional on robot exposure (see column (6) of table 2.C.6), indicating that high-skilled workers are able to find new jobs in the local economy. The bottom panel of table 2.C.6 further shows small negative wage effects for all skill groups, though the decline is strongest and most significant for low-skilled workers. These negative wage effects indicate that local labor markets have not experienced sizable productivity gains through the diffusion of AI into the economy yet.

Robots, in turn, mostly replaced low-skilled workers in exposed firms. The top panel of table 2.C.6 confirms this result at the local labor market level: robots primarily automate jobs of low-skilled workers, and these are not easily absorbed into other industries in the local economy. Again in line with the firm-level evidence, robots increase the demand for medium-skilled workers (column (6)). Interestingly, we see little effect on high-skill employment in the local economy though the effect was positive at the plant level. The difference indicates that plants exposed to robots seem to satisfy their additional need for high-skilled specialists by luring them away from other industries in the local economy with little net upskilling in the region. The bottom panel of table 2.C.6 shows few wage responses once we condition on AI exposure.

Overall, the evidence at the plant and local labor market level shows that robots have a strong skill bias. While skilled workers are complements to robots, less-skilled workers are substituted. AI, in turn, has no such skill bias as it appears to mostly reduce the employment of more skilled workers. The negative firm-level impact for high-skilled workers is compensated by good employment prospects in other industries.

Our findings paint a nuanced picture of the impact of different digital technologies on the labor market. Robots, with their strong automation potential for low-skilled jobs, have different effects than AI technologies, which seem to replace workers higher up the skill distribution. When discussing the economic consequences and policy implications of the digital transition, it is therefore important not to extrapolate from one technology to another.

2.6 Robustness Checks

We conduct a series of robustness checks to provide additional evidence on the stability of the results we find. First, for our estimation at the firm level, we use different specifications for our independent variables that capture robot and AI exposure. Next, we re-estimate equations 2.3 and 2.5 at the firm and district level while excluding German patents.

To rule out that our results are driven by the definition of our industry-level technology exposure measures, we estimate equation 2.3 with three alternative definitions of AI and robot exposure. First, we use the raw count of patents instead of log-transforming them. The second specification applies the inverse hyperbolic sine transformation. The third specification uses a log transformation, for which we add 0.1 to the patent count instead of using $log(1 + patents)$ as before. As shown in table 2.D.5, the results are qualitatively similar to our main results.

In our main specification of the shift-share instrument, we include all patents filed at the EPO over the sample period. This also includes patents filed by German inventors. However, there might be concerns that patenting in Germany is endogenously related to local labor market conditions, and therefore, the exogeneity assumption of the shift variable is threatened. To test for this, we construct a separate measure of exposure to AI and robotics that excludes all patents filed by German inventors. The share of German patents among all patents filed is 11% for AI and 14% for robotics patents. We drop these patents and continue to construct the district-level exposure in the same way as before. The results for firm-level employment and wages are reported in column (4) of table 2.D.5 in the appendix. The results for district-level employment and wages are reported in table 2.D.6. Running the same set of regressions as previously but using the new exposure measure, we find that our results are largely robust to excluding German patents.

2.7 Conclusion

We develop new measures for the advancement of robotics and AI technologies in Europe, applying natural language processing on patent data from the European Patent Office. Our measures for robotics are strongly correlated with robot installations but are available for more industries in manufacturing as well as outside manufacturing compared to existing data on industrial robots. Our measure for AI technologies shows a positive correlation with the share of firms that have AI knowledge in a given industry. They are also positively correlated with AI-related job vacancies. Overall, knowledge in robotics technology has been more prominent over the 1990-2018 period but has diffused into a small set of industries in Germany. The patenting of knowledge in AI technologies, in turn, has only picked up since 2015 but has started to diffuse into more industries. We then use our new measures to explore the labor market consequences of the new technologies. Using panel data on German establishments, we first investigate effects on the plant level and find that AI exposure is associated with a decline in overall employment and a small increase in wages. Robot exposure leads to net zero or positive employment effects but no corresponding wage increase. The firm level employment and wage effects differ considerably between workers by skill level. AI leads to decreased employment at all skill levels, whereas robot exposure leads to a decrease in employment of low-skilled workers but an increase in employment of medium- and high-skilled workers. These results are average effects at the industry level, including active adopters of new technologies and their competitors. We are, therefore, estimating the net effects of technology exposure on employment and wages.

Next, we turn to local labor markets as the unit of analysis. Aggregating our German plant-level data to the district level and using a shift-share approach, we find that exposure to AI reduces local employment and wages while robots have a small positive effect on employment and few effects on local wages.

Most importantly, the small average effects mask considerable heterogeneities across sectors of the economy: employment declines are much more pronounced in manufacturing than in the service sector. We also investigate what happens if we control for both types of technologies simultaneously. These conditional estimates indicate that AI technologies have stronger negative employment effects in manufacturing than in services, while districts with high robot exposure see a small increase in service sector employment and insignificant effects on manufacturing employment.

Finally, we investigate how different skill groups are affected by the new technologies. The negative employment effects of AI exposure are concentrated on medium- and low-skilled workers, while the negative wage effects persist for all skill groups. The diffusion of robotics technology hits low-skilled workers hardest, decreasing low-skilled jobs but increasing the employment of medium-skilled workers.

Our results for robotics are consistent with earlier evidence using installations as a direct measure of robot diffusion in manufacturing (Dauth et al., 2021) that finds negative employment effects with considerable heterogeneities between worker groups. However, in our setting, increasing employment in services does not compensate for these negative effects. The consistency of results for the two measures provides additional support for our approach to proxy the advancement of digital technologies using patent data. For AI, our approach provides a novel measure at the industry level over three decades, which complements recent attempts to quantify the future automation potential at the occupation level. Unlike previous studies that consider AI and robotics jointly as automation technologies (see Mann and Püttmann (2023) for example), we find considerable differences in the labor market effects of the two technologies, especially if we consider differences across skill groups. The most likely explanation is that they are used differently in production and vary in how they substitute for or enhance human labor.

2.A Details on Construction of Patent Measures

Our data come from the World Patent Statistical Database (PATSTAT), which contains detailed bibliographical and technical information on all patents filed in eighty-six countries. The data on patent applications and grants at the EPO contain a total of about 7 million patent documents, which are identified by 3.5m unique application ids.[14] Of the 7 million documents, 5 million are patent applications, and about 2 million are patent grants.

To determine whether a patent covers an innovation in the field of AI or robotics, we analyze the titles and abstracts of patents. Though each patent document includes a title, abstracts are missing for about 30% of the patent grants (670,000 cases) we extracted. Instead of dropping those patents, we use the concept of patent families to impute an abstract that describes the technical content of a patent. A patent family is defined based on patents with the same (detailed or slightly broader) IPC/CPC code. Each patent belongs to a narrow patent family, which covers all patents with the same technical content, and also to an extended patent family of all patents with similar technical content. As the patent classification of technologies is very detailed, the technical content is very similar, even within an extended patent family. We first use abstracts from the same narrow patent family to impute missing abstracts; if that is not successful, we use the extended patent family instead. Following this procedure, we can impute about 450,000 abstracts, of which only 45,262 abstracts are based on the extended patent family. We drop the remaining patents for which we could not impute an abstract.

A patent can be filed at the EPO in one of the three official languages: English, French, and German. Patents filed in another language need to provide a translation into one of the official ones. While patent claims are published in all three languages, abstract and patent description are published in the official language the patent

[14]The smaller number of unique applications reflects the fact that most patents have multiple entries in the PATSTAT database, one for the patent application, others for revisions and yet another for the patent grant if the patenting process was successful.

was filed in. We restrict attention to documents with an abstract in English as other languages are not compatible with our keyword search.[15]

We use a combination of patent classification codes (IPC/CPC) and keyword searches of the patent title and abstract to identify patents related to robotics and AI. A patent is then classified as a match for robotics if one or more keyword tokens match with tokens of the text corpora of titles and abstracts.

As a second step, we conduct a keyword search over the titles and abstracts of all remaining patents based on a keyword list compiled from the World Intellectual Property Organization (2019) and Baruffaldi et al. (2020). Examples of keywords include machine learning, natural language processing, fuzzy logic, or decision tree.[16] The keyword list is pre-processed using the same steps as for the patent documents. A patent is classified as a match for AI technologies if one or more keyword tokens match with tokens of the text corpora of titles and abstracts. Figures 2.D.7 and 2.D.8 in the appendix show examples of a robot and an AI patent application with highlighted keyword matches in their title and abstract. The examples show that patent titles often include specific terms like neural networks, while the abstract contains more general technological concepts such as artificial intelligence or machine learning.

For robotics, our search yields 14,235 patent documents of which 92% contain one or more of the keywords and 8% are included based on the CPC code 'B25J9'. Around 11,000 are actual applications or grants; the remainder contain supplementary information to existing applications.[17] For AI technologies, the combined approach of codes and keyword search yields 10,311 patent documents, of which 90% contain one or more of the AI-specific keywords and 10% are included purely on their

[15] PATSTAT typically records the language of the abstract, but this information is missing for about 250,000 patent documents. We use natural language processing to identify the language of the abstract for documents missing that information. We then drop all documents that do not contain any information in English, which reduces our sample by only 7%.

[16] Our keyword list is shorter than the list used in World Intellectual Property Organization (2019) in order to reduce false positives. Their keyword list includes keywords like network, algorithm, logic, and boost, which can potentially be found in many patents that are unrelated to AI technologies.

[17] Such supplementary documents can be corrections to existing applications or supporting material such as search reports.

CPC codes. After excluding supplementary documents, we are left with around 7,000 applications and grants.

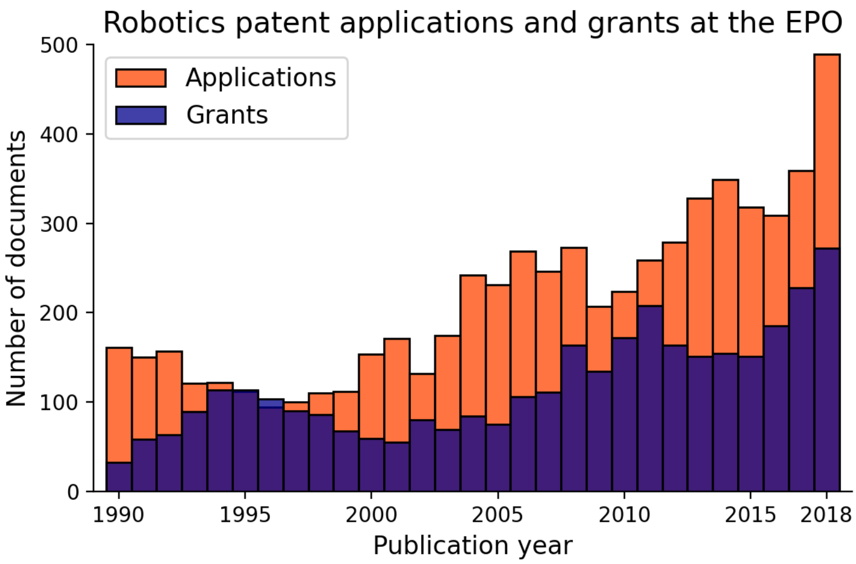
To provide first descriptive evidence in which sectors of the economy AI and robotics innovations are patented, we aggregate patents to broader technology classes. We use a mapping of the more recent IPC codes at the 4-digit level to thirty-five technology classes developed by Schmoch (2008).[18] We then aggregate the thirty-five technology classes into five broad sectors: Electrical engineering, Mechanical engineering, Instruments, Chemistry and Other fields. Instruments include optical instruments, control technology and medical technology. Chemicals include pharmaceuticals, biotechnology, food and materials. Other includes many consumption goods like furniture, games but also civil engineering.

[18]We prefer this classification over the one in Hall et al. (2001) because the latter is much older and thus less accurate in capturing recent developments in AI and robotics.

2.B Figures

Figure 2.B.1: Number of Patents in AI and Robotics, 1990-2018

(a) Robotics Patents



(b) AI Patents

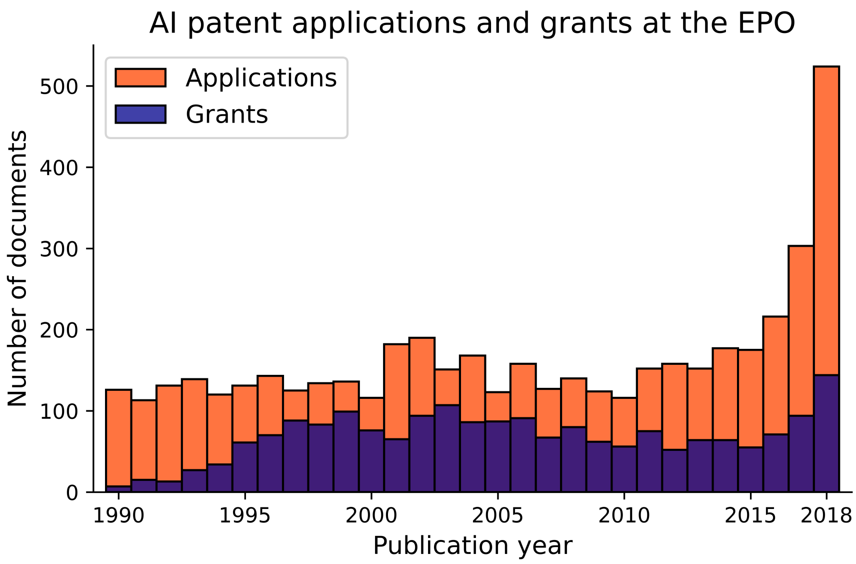


Figure 2.B.2: Cumulative log AI patents by industry

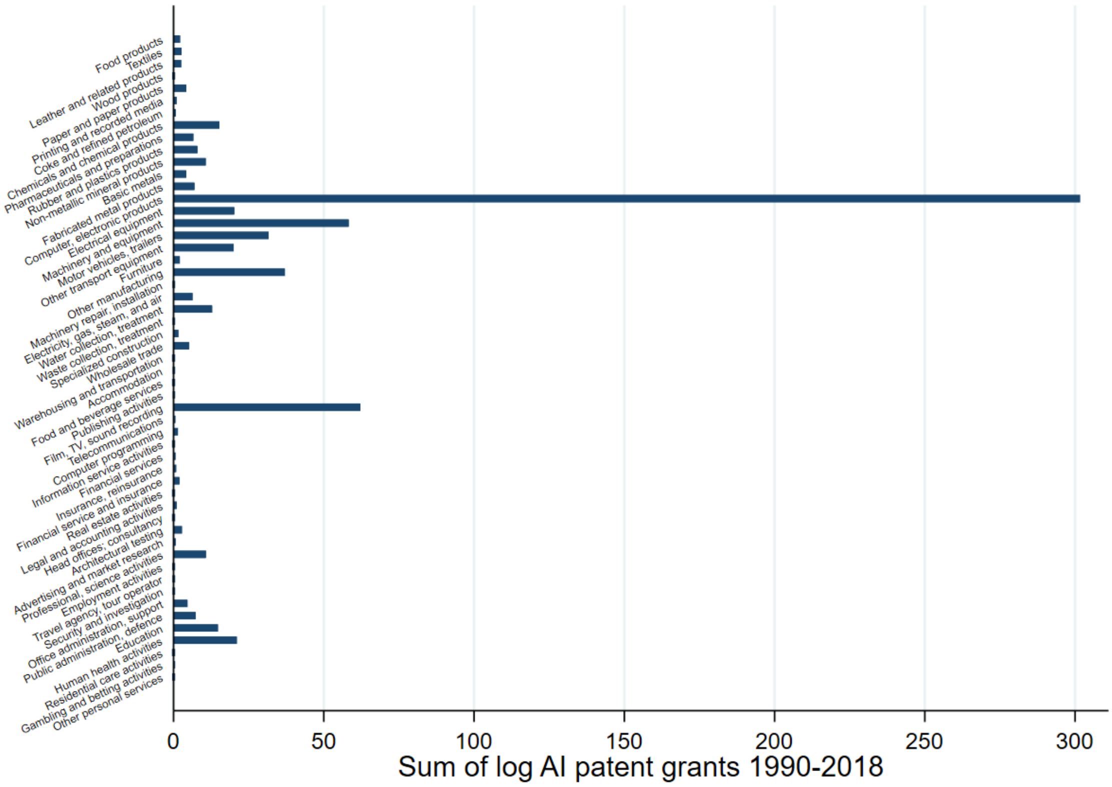


Figure 2.B.3: Cumulative log robot patents by industry

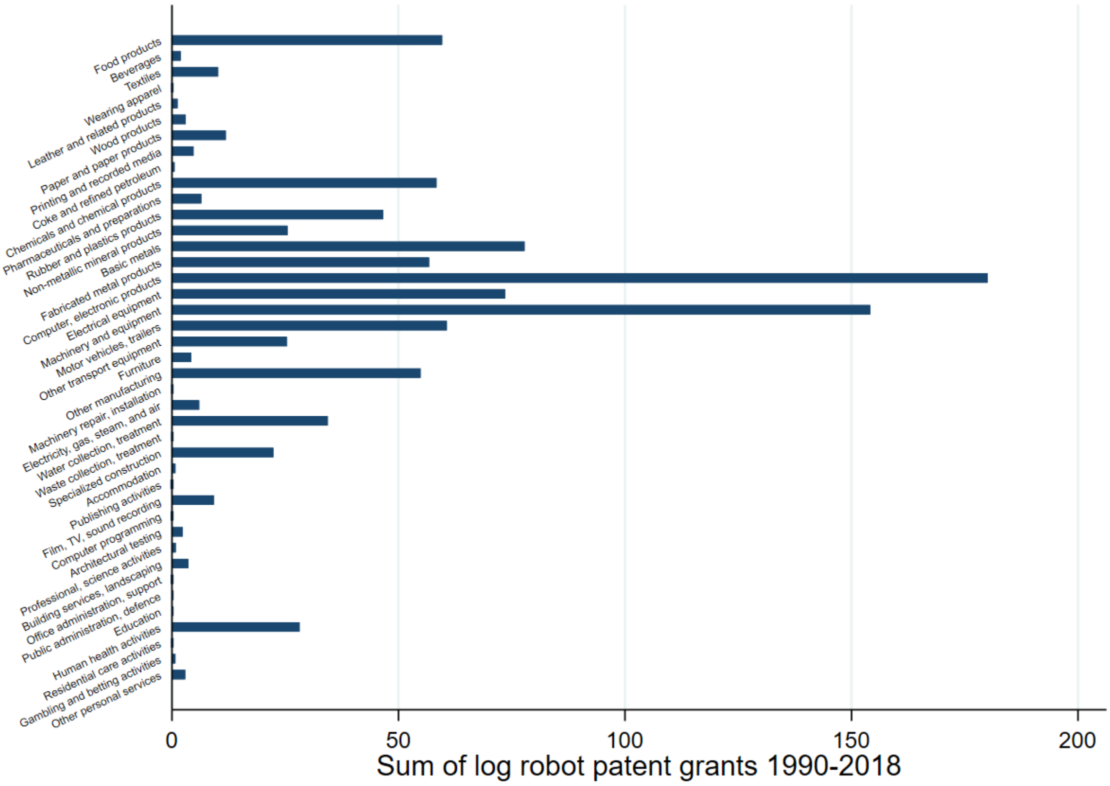
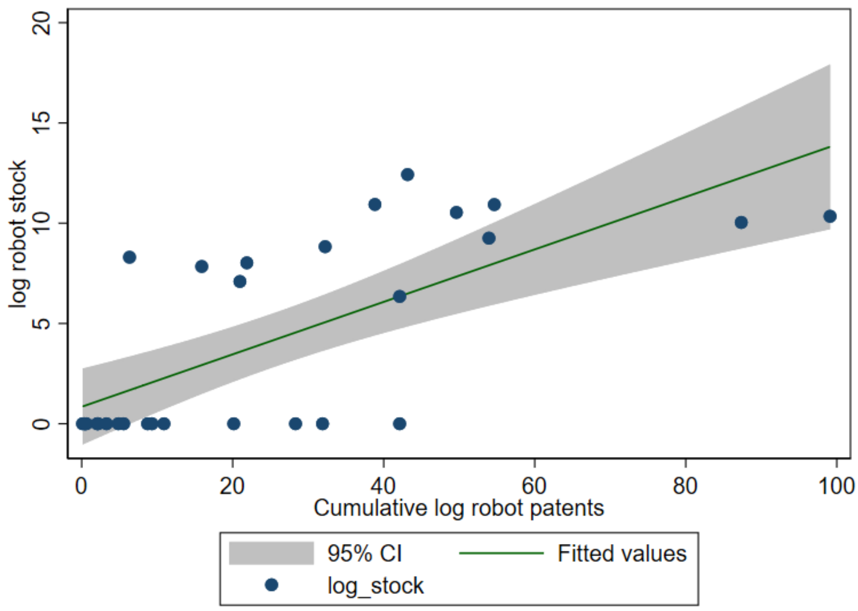
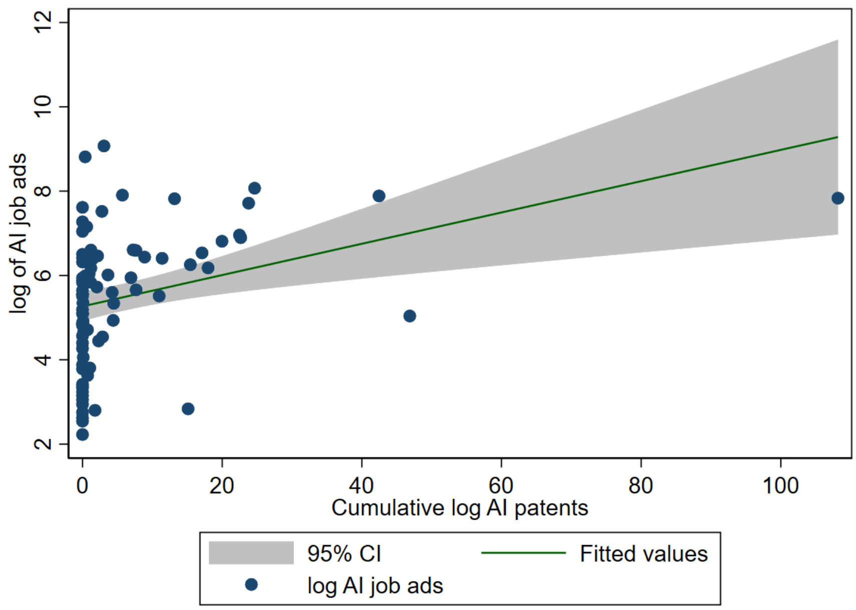


Figure 2.B.4: Correlation of Robot Stock and Patents

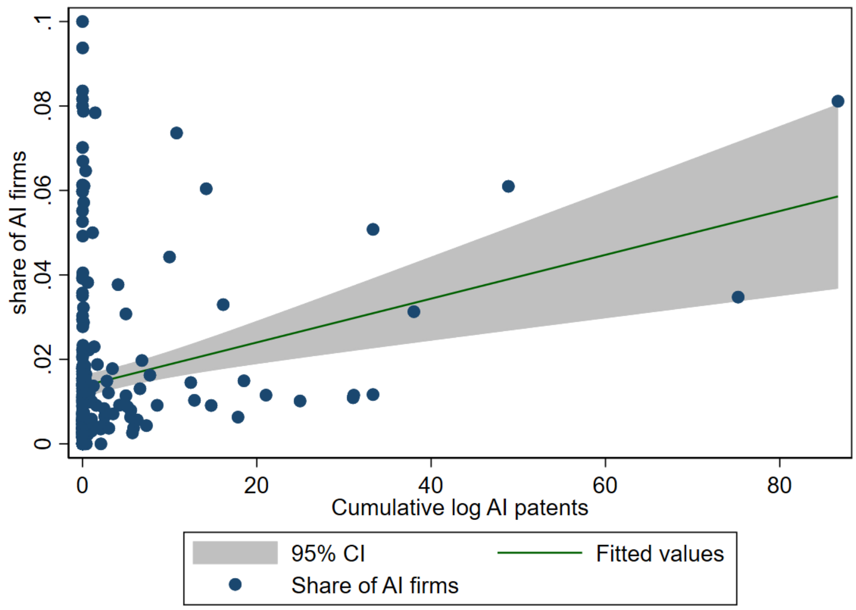


Patents are measured as cumulative sum of log patents until 2018. The stock of robots is measured in logs in 2018. Both measures are at the level of industries. The industry classification follows the International Federation of Robotics.

Figure 2.B.5: Correlation of AI Patents, AI Firms and AI Job Vacancies



(a) AI Skills in Online Job Ads and AI patents

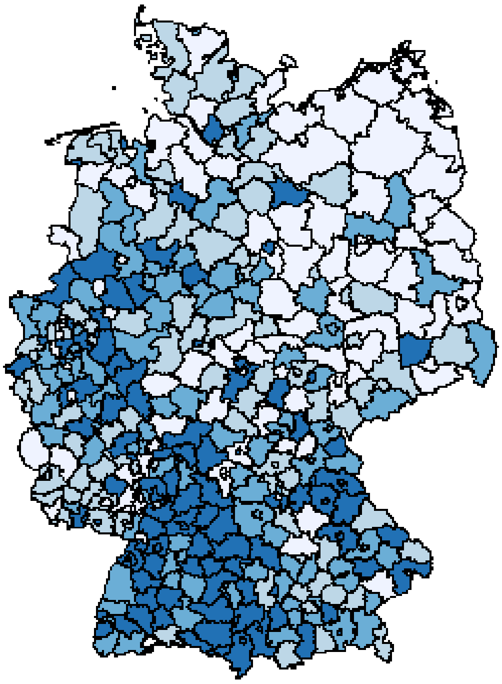


(b) AI firms and AI patents

Patents are measured as cumulative sum of log patents until 2018. Panel a) plots the number of vacancies that require at least one AI skill per industry (based on online job vacancy data for Germany in 2021) against our AI patent measure. Panel b) plots the share of firms using or developing AI at the 3-digit industry level in Germany (based on data on company websites from Istari.ai in 2022).

Figure 2.B.7: Regional Cumulative Exposure to AI and Robotics in 2018

(a) AI exposure



(b) Robot exposure

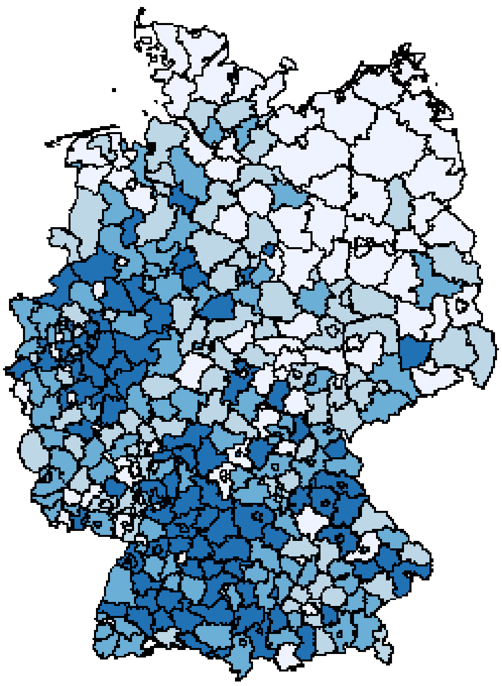
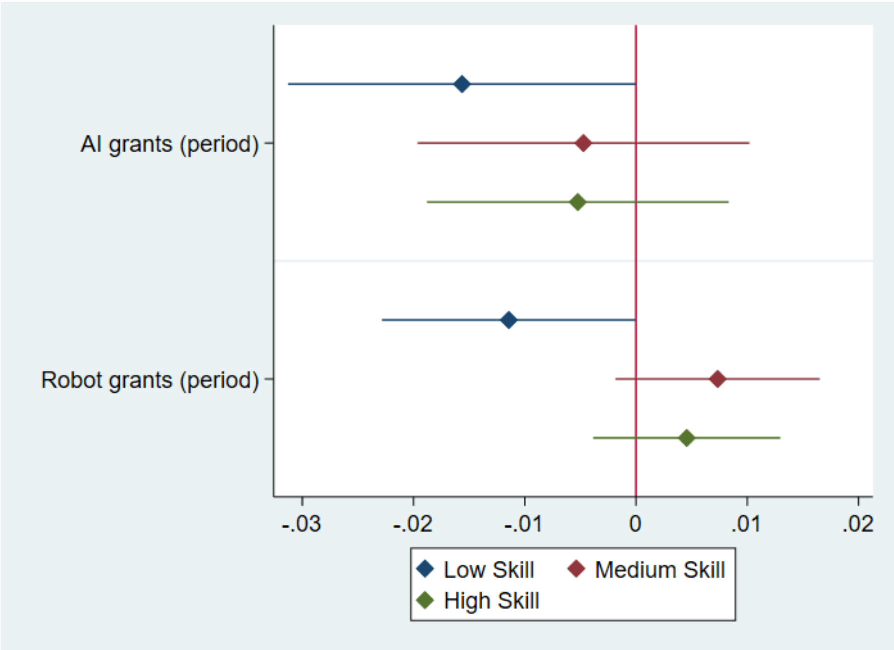
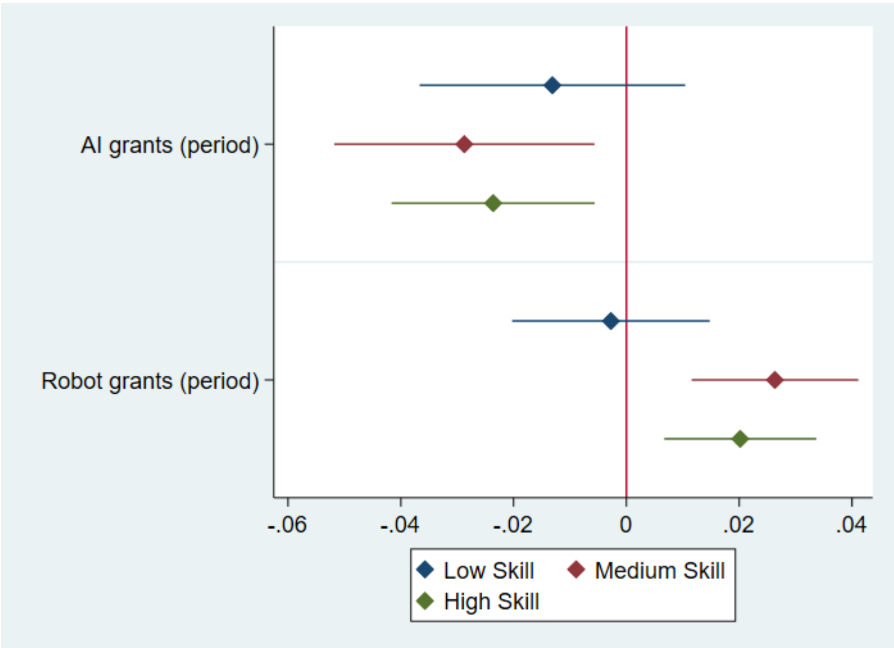


Figure 2.B.8: Firm Level Employment Effects of AI and Robots by Skill



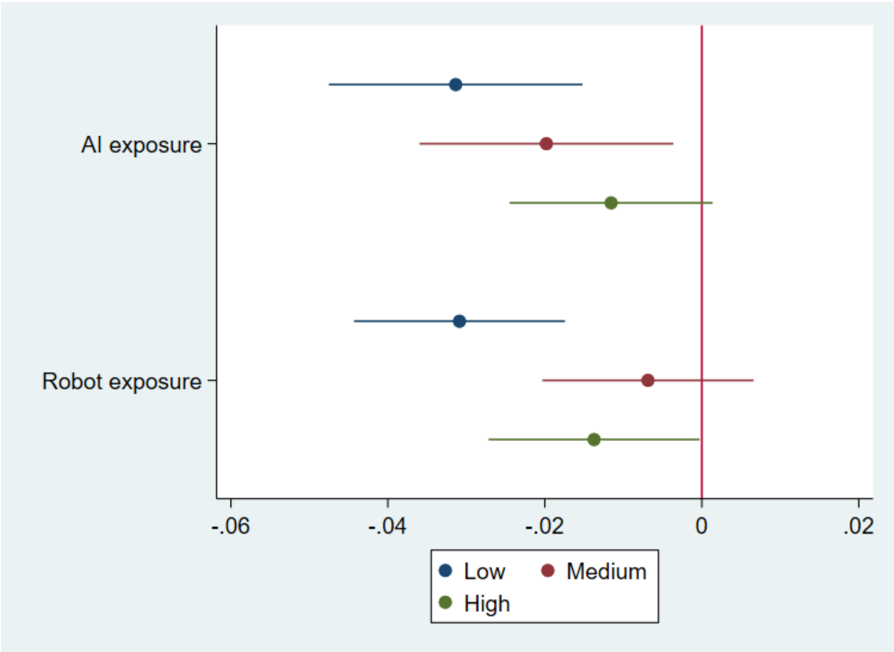
(a) AI and Robots separately



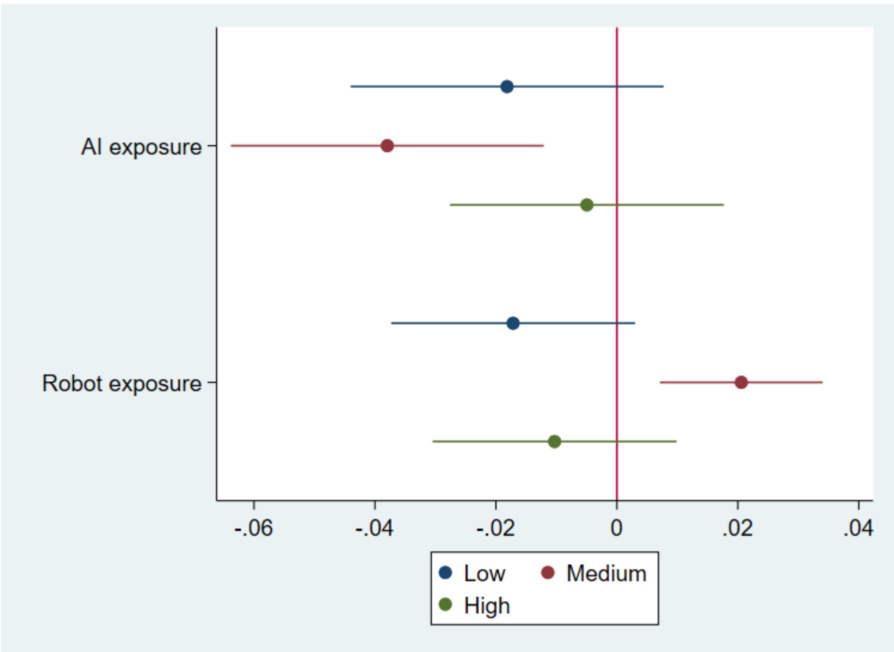
(b) AI and Robots jointly

The plots depict coefficients estimated according to equation (3). All coefficients and standard errors are scaled by one standard deviation of the independent variables.

Figure 2.B.10: District Level Employment Effects of AI and Robots by Skill



(a) AI and Robots separately



(b) AI and Robots jointly

The plots depict coefficients estimated according to equation (4). All coefficients and standard errors are scaled by one standard deviation of the independent variables.

2.C Tables

Table 2.C.1: Plant-level Employment and Wage Effects

	(1) Employment	(2) Employment	(3) Employment	(4) Wages	(5) Wages	(6) Wages
AI grants (period)	-0.001		-0.005*	0.003***		0.004***
	(0.002)		(0.003)	(0.001)		(0.001)
Robot grants (period)		0.000	0.002**		0.001***	-0.001**
		(0.001)	(0.001)		(0.000)	(0.000)
Initial employment	Yes	Yes	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4114689	4114689	4114689	2823570	2823570	2823570

Notes: The table reports estimates from equation (2.3), where the dependent variables are average log employment or wages in four sub-periods. The AI and robot measures are defined as in equation (2.1). Controls include initial period employment, ICT investment and net exports. Regressions are weighted by establishment size. All models include establishment and period fixed effects. Standard errors are clustered at the industry#period level and are reported in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 2.C.2: Plant-level Employment and Wages by Skill

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Low-Skill Employment			**Medium-Skill Employment**			**High-Skill Employment**		
AI	-0.005*		-0.004	-0.001		-0.008**	-0.002		-0.007**
	(0.002)		(0.003)	(0.002)		(0.003)	(0.002)		(0.003)
Robots		-0.002**	-0.000		0.001	0.004***		0.001	0.003***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Observations	4114689	4114689	4114689	4114689	4114689	4114689	4114689	4114689	4114689
	Low-Skill Wages			**Medium-Skill Wages**			**High-Skill Wages**		
AI	0.001		0.002***	0.002***		0.003***	0.002**		0.003***
	(0.001)		(0.001)	(0.000)		(0.001)	(0.001)		(0.001)
Robots		-0.000	-0.001***		0.000	-0.001**		0.000	-0.001***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Observations	771011	771011	771011	2620551	2620551	2620551	931590	931590	931590
Initial employment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Net exports	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates from equation (2.3), where the dependent variables are average log wages by skill groups in four sub-periods. The AI and robot measures are defined as in equation (2.1). Controls include initial period employment, ICT investment and net exports. Regressions are weighted by establishment size. All models include establishment and period fixed effects. Standard errors are clustered at the industry#period level and are reported in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 2.C.3: Plant-level Employment and Wage Effects in Manufacturing and Services

Panel A: Employment	(1) Manufacturing	(2) Manufacturing	(3) Manufacturing	(4) Services	(5) Services	(6) Services
AI grants (period)	0.000		-0.005	0.003		-0.006
	(0.003)		(0.004)	(0.003)		(0.005)
Robot grants (period)		0.002**	0.004**		0.005***	0.009***
		(0.001)	(0.002)		(0.002)	(0.003)
Initial employment	Yes	Yes	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	353583	353583	353583	3640460	3640460	3640460
Panel B: Wages						
	(1)	(2)	(3)	(4)	(5)	(6)
	Manufacturing	Manufacturing	Manufacturing	Services	Services	Services
AI grants (period)	0.003***		0.005***	0.002**		-0.001
	(0.001)		(0.001)	(0.001)		(0.001)
Robot grants (period)		0.000	-0.001***		0.002***	0.003***
		(0.000)	(0.000)		(0.001)	(0.001)
Initial employment	Yes	Yes	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	309330	309330	309330	2427422	2427422	2427422

Notes: The table reports estimates from equation (2.3), where the dependent variables are average log employment or wages in four sub-periods. The AI and robot measures are defined as in equation (2.1). Controls include initial period employment, ICT investment and net exports. Regressions are weighted by establishment size. Effects are estimated separately in manufacturing or services industries. All models include establishment and period fixed effects. Standard errors are clustered at the industry#period level and are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 2.C.4: District Employment and Wage Effects

	(1) Δ Employment	(2) Δ Employment	(3) Δ Employment	(4) Δ Wages	(5) Δ Wages	(6) Δ Wages
AI grants (period-district)	-0.011**		-0.018**	-0.009***		-0.008*
	(0.004)		(0.007)	(0.003)		(0.005)
Robot grants (period-district)		-0.002	0.004**		-0.003***	-0.001
		(0.001)	(0.002)		(0.001)	(0.002)
Net exports	Yes	Yes	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1600	1600	1600	1600	1600	1600

Notes: The table reports estimates from equation (2.5) where the dependent variables are log employment (columns (1) to (3)) or wage changes (columns (4) to (6)) in four sub-periods. The exposure measures are shift share variables as defined in equation (2.4). Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers. All demographic control variables refer to the first year of the respective sub-period. Industry employment shares are measured at the one-digit level in the base year. Net exports are measured at the one-digit industry level, adjusted by the total wage bill. ICT investment is measured per worker at the one-digit industry level. All models include district- and period fixed effects. Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 2.C.5: District Employment and Wage Effects in Manufacturing and Services

Panel A: Employment	(1) Manufacturing	(2) Manufacturing	(3) Manufacturing	(4) Services	(5) Services	(6) Services
AI grants (period-district)	-0.027***		-0.032*	-0.004		-0.010**
	(0.010)		(0.019)	(0.003)		(0.005)
Robot grants (period-district)		-0.009***	0.003		-0.000	0.004*
		(0.003)	(0.006)		(0.001)	(0.002)
Net exports	Yes	Yes	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1600	1600	1600	1600	1600	1600

Panel B: Wages	(1) Manufacturing	(2) Manufacturing	(3) Manufacturing	(4) Services	(5) Services	(6) Services
AI grants (period-district)	-0.007**		-0.003	-0.002		-0.003
	(0.003)		(0.005)	(0.001)		(0.002)
Robot grants (period-district)		-0.003***	-0.003		-0.001	0.000
		(0.001)	(0.002)		(0.001)	(0.001)
Net exports	Yes	Yes	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1600	1600	1600	1600	1600	1600

Notes: The table reports estimates from equation (2.5) where the dependent variables are log employment (Panel A) or wage changes (Panel B) in Manufacturing (columns (1) to (3)) or Services (columns (4) to (6)) in four sub-periods. The exposure measures are shift share variables as defined in equation (2.4). Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers. All demographic control variables refer to the first year of the respective sub-period. Industry employment shares are measured at the one-digit level in the base year. Net exports are measured at the one-digit industry level, adjusted by the total wage bill. ICT investment is measured per worker at the one-digit industry level. All models include district- and period fixed effects. Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 2.C.6: District Employment and Wage Effects by Skill Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Low-Skill Employment			**Medium-Skill Employment**			**High-Skill Employment**		
AI grants (period-district)	-0.019***		-0.011	-0.012**		-0.023***	-0.007*		0.003
	(0.005)		(0.008)	(0.005)		(0.008)	(0.004)		(0.007)
Robot grants (period-district)		-0.009***	-0.005		-0.002	0.006***		-0.004**	-0.003
		(0.002)	(0.003)		(0.002)	(0.002)		(0.002)	(0.003)
	Low-Skill Wages			**Medium-Skill Wages**			**High-Skill Wages**		
AI grants (period-district)	-0.009***		-0.014***	-0.008***		-0.004	-0.007**		-0.005
	(0.003)		(0.004)	(0.002)		(0.003)	(0.003)		(0.005)
Robot grants (period-district)		-0.002*	0.003		-0.004***	-0.002		-0.003**	-0.001
		(0.001)	(0.002)		(0.001)	(0.002)		(0.001)	(0.002)
Observations	1600	1600	1600	1600	1600	1600	1600	1600	1600
Initial employment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Net exports	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates from equation (2.5) where the dependent variables are log employment and wage changes by skill groups (low-, medium- and high-skill) in four sub-periods. The exposure measures are shift share variables as defined in equation (2.4). Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers. All demographic control variables refer to the first year of the respective sub-period. Industry employment shares are measured at the one-digit level in the base year. Net exports are measured at the one-digit industry level, adjusted by the total wage bill. ICT investment is measured per worker at the one-digit industry level. All models include district- and period fixed effects. Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

2.D Additional Results

Table 2.D.1: Top Using Industries of AI and Robotics Patents

ISIC	Industry	AI Patents	% AI Grants in Industry
2620	Computers and peripheral equipment	582	1.49
2640	Consumer electronics	316	4.45
2630	Communication equipment	139	0.55
2817	Office machinery and equipment	138	2.00
2822	Metal-forming machinery and machine tools	74	0.86
2670	Optical instruments and photographic equipment	72	0.25
5912	Motion picture, video and television programme post-production activities	69	0.47
5920	Sound recording and music publishing activities	65	0.24
2651	Measuring, testing, navigating and control equipment	52	0.35
8620	Medical and dental practice activities	40	0.18
ISIC	Industry	Robotics Patent	% Robotics Patents in Industry
2814	Bearings, gears, gearing and driving elements	413	1.80
2822	Metal-forming machinery and machine tools	228	2.63
2651	Measuring, testing, navigating and control equipment	169	1.13
2750	Domestic appliances	148	1.15
2592	Treatment and coating of metals	138	1.89
2811	Engines and turbines	137	0.41
1050	Dairy products	137	4.93
2816	Lifting and handling equipment	117	0.82
2670	Optical instruments and photographic equipment	101	0.36
2620	Computers and peripheral equipment	97	0.24

Notes: The table reports the top ten four-digit industries using AI (top panel) and robotics patents (bottom panel). The second column reports the total number of patent grants used in the industry during the 1990-2018 period, while the last column reports the share of AI resp. robotics patents to all patents used in the industry.

Table 2.D.2: Industries with Strongest Growth in AI and Robotics Patents

ISIC	Industry	Growth in AI Patents
262	Manufacture of computers and peripheral equipment	5.76
264	Manufacture of consumer electronics	3.71
862	Medical and dental practice activities	3.70
263	Manufacture of communication equipment	3.53
267	Manufacture of optical instruments and photographic equipment	3.36
265	Manufacture of measuring, testing, navigating and control equipment; watches and clocks	3.26
592	Sound recording and music publishing activities	3.01
281	Manufacture of general-purpose machinery	2.76
282	Manufacture of special-purpose machinery	2.52
749	Other professional, scientific and technical activities	2.43
ISIC	Industry	Growth in Robotics Patents
862	Medical and dental practice activities	4.35
267	Manufacture of optical instruments and photographic equipment	3.36
262	Manufacture of computers and peripheral equipment	3.32
325	Manufacture of medical and dental instruments and supplies	3.00
105	Manufacture of dairy products	2.74
360	Water collection, treatment and supply	2.52
310	Manufacture of furniture	2.40
202	Manufacture of other chemical products	2.17
960	Other personal service activities	2.11
201	Manufacture of basic chemicals, fertilizers and nitrogen compounds, plastics and synthetic rubber	2.11

Notes: The table reports the top ten four-digit industries using AI (top panel) and robotics patents (bottom panel). The second column reports the total number of patent grants used in the industry during the 1990-2018 period, while the last column reports the share of AI resp. robotics patents to all patents used in the industry.

Table 2.D.3: Plant Characteristics and Exposure Measures

	Obs	Mean	Std. Dev.	Min	Max
Outcome variables:					
Log Employment	8,321,322	1.4747	.9555	.6931	11.0850
Log Wage	4,972,440	4.1733	.5638	.0091	7.9354
Log Low-skill Employment	8,321,322	.4075	.6447	0	8.9658
Log Medium-skill Employment	8,321,322	1.1882	.9550	0	10.6056
Log High-skill Employment	8,321,322	.2966	.6154	0	10.0408
Log Low-skill Wage	1,478,332	4.0285	.5660	.0102	7.3965
Log Medium-skill Wage	4,469,474	4.1755	.5279	.0099	8.2739
Log High-skill Wage	1,585,626	4.5769	.6043	.0095	8.0878
Exposure Measures:					
Δ Log AI Exposure	8,321,322	.8506	3.4321	0	86.6775
Δ Log Robot Exposure	8,321,322	1.3396	6.1234	0	89.3207
Control variables:					
Initial Employment	5,580,252	12.0833	94.3619	1	64192
Δ Net exports	8,321,322	.9137	1.3013	0	9.5718
Δ ICT investment	8,321,322	6.78e09	4.04e10	-2.00e10	3.20e11

Notes: The outcome and exposure measures are measured at the plant-period level where plants are observed in up to four periods. Employment and wage variables are measured as averages per period in logs. The exposure measures are shift-share variables consisting of two components: the shift variable denotes the cumulative number of patents in robotics and AI technologies used in a certain industry. The information on patents is extracted from EPO data using natural language processing techniques. The share variable is the employment share of an industry in the district in 1993. Control variables are the initial plant employment in the beginning of each period, net exports and ICT investment. Exports and ICT capital are measured at the 1-digit industry-period level.

Table 2.D.4: Local Labor Market Characteristics and Exposure Measures

	Obs	Mean	Std. Dev.	Min	Max
Outcome variables:					
Δ Log Employment	1,600	.0379	.0674	-.3544	.7433
Δ Log Daily Wage	1,600	.0233	.0596	-.2626	.5239
Δ Log Low-skill Employment	1,600	-.0463	.1129	-.7451	.7997
Δ Log Medium-skill Employment	1,600	.0222	.0721	-.4413	.7976
Δ Log High-skill Employment	1,600	.1671	.1183	-.3402	1.1161
Δ Log Low-skill Wage	1,600	.0298	.0708	-.2850	.5477
Δ Log Medium-skill Wage	1,600	.0184	.0541	-.2912	.2462
Δ Log High-skill Wage	1,600	.0078	.0628	-.2756	.4627
Exposure Measures:					
Δ Log AI Exposure	1,600	1.9600	1.6582	.1228	14.9378
Δ Log Robot Exposure	1,600	4.8075	3.8214	.1998	32.5569
Control variables:					
% High-skilled Workers	1,600	.1068	.0501	.0253	.3726
% Medium-skilled Workers	1,600	.7250	.0549	.4776	.8442
% Low-skilled Workers	1,600	.1399	.0429	.0344	.3012
% Female Employment	1,600	.4907	.0394	.2655	.6357
% Workers aged 20-34	1,600	.2874	.0377	.2007	.4312
% Workers aged 35-49	1,600	.3815	.0438	.2788	.5196
% Workers aged 50-64	1,600	.2596	.0607	.1479	.4314
Δ Net exports	1,600	1.13e10	1.50e10	-5.97e10	1.34e11
Δ ICT investment	1,600	1.179339	.2743092	.7140896	2.673793

Notes: The outcome and exposure measures are measured at the district-period level. Each of the 400 districts is observed in four periods. Changes are calculated as log changes between the first and last year of each period. The exposure measures are shift-share variables consisting of two components: the shift variable denotes the cumulative number of patents in robotics and AI technologies used in a certain industry. The information on patents is extracted from EPO data using natural language processing techniques. The share variable is the employment share of an industry in the district in 1993. All control variables are measured at the district-period level and represent employment shares at the beginning of each period. Additional controls not depicted in the table are employment shares by 1-digit industries at the district-period level.

Table 2.D.5: Plant-level Robustness Checks

Panel A: Employment	(1) Raw counts	(2) IHS transformation	(3) log(0.1 +) transformation	(4) No German patents
AI exposure	-0.00078	-0.00391	-0.00047	-0.005
	(0.00053)	(0.00245)	(0.00078)	(0.003)
Robot exposure	0.00017	0.00188*	0.00094	0.002*
	(0.00012)	(0.00096)	(0.00058)	(0.001)
Initial employment	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes
Net exports	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Observations	4114689	4114689	4114689	4114689

Panel B: Wages	(1) Raw counts	(2) IHS transformation	(3) log(0.1 +) transformation	(4) No German patents
AI exposure	0.00059***	0.00255***	0.00025	0.003***
	(0.00017)	(0.00054)	(0.00027)	(0.001)
Robot exposure	0.00001	-0.00043*	0.00009	-0.000
	(0.00002)	(0.00024)	(0.00018)	(0.000)
Initial employment	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes
Net exports	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Observations	2823570	2823570	2823570	2823570

Notes: The table reports estimates from equation (2.3), where the dependent variables are average log employment or wages in four sub-periods. The table presents alternative definitions of the main independent variables AI and robot exposure. Column (1) uses raw patent counts, column (2) uses the inverse hyperbolic sine transformation, and column (3) uses a log(0.1 + patents) transformation. In column (4), patents of German inventors are excluded. Controls include initial period employment, ICT investment and net exports. Regressions are weighted by establishment size. All models include establishment and period fixed effects. Standard errors are clustered at the industry#period level and are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 2.D.6: District Employment and Wage Effects - No German patents

	(1) Δ Employment	(2) Δ Employment	(3) Δ Employment	(4) Δ Wages	(5) Δ Wages	(6) Δ Wages
AI grants (period-district)	-0.012**		-0.017**	-0.010***		-0.008*
	(0.005)		(0.007)	(0.003)		(0.005)
Robot grants (period-district)		-0.003*	0.003		-0.004***	-0.001
		(0.001)	(0.002)		(0.001)	(0.002)
Net exports	Yes	Yes	Yes	Yes	Yes	Yes
ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1600	1600	1600	1600	1600	1600

Notes: The table reports estimates from equation (2.5) where the dependent variables are log employment (columns (1) to (3)) or wage changes (columns (4) to (6)) in four sub-periods. The exposure measures are shift share variables as defined in equation (2.4). All patents from German inventors are excluded. Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers. All demographic control variables refer to the first year of the respective sub-period. Industry employment shares are measured at the one-digit level in the base year. Net exports are measured at the one-digit industry level, adjusted by the total wage bill. ICT investment is measured per worker at the one-digit industry level. All models include district- and period fixed effects. Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Figure 2.D.7: Example of a robot patent document with highlighted keyword matches

(19) Europäisches Patentamt
European Patent Office
Office européen des brevets

(11) **EP 2 965 874 A2**

(12) **EUROPEAN PATENT APPLICATION**

(43) Date of publication:
13.01.2016 Bulletin 2016/02

(51) Int Cl.:
B25J 9/16 *(2006.01)* ***B25J 19/06*** *(2006.01)*

(21) Application number: **15171225.4**

(22) Date of filing: **09.06.2015**

(84) Designated Contracting States:
AL AT BE BG CH CY CZ DE DK EE ES FI FR GB GR HR HU IE IS IT LI LT LU LV MC MK MT NL NO PL PT RO RS SE SI SK SM TR
Designated Extension States:
BA ME
Designated Validation States:
MA

(30) Priority: **10.06.2014 JP 2014119369**

(71) Applicant: **CANON KABUSHIKI KAISHA**
Ohta-ku
Tokyo 146-8501 (JP)

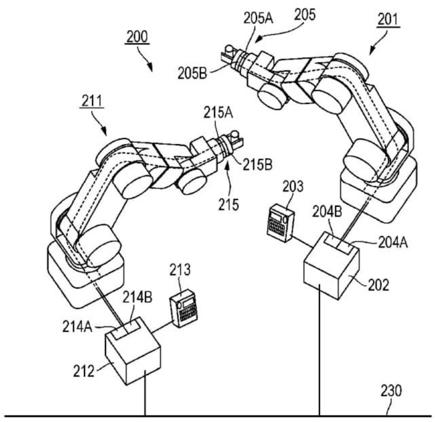
(72) Inventor: **IIZUKA, Shinsuke**
Ohta-ku, Tokyo (JP)

(74) Representative: **Houle, Timothy James**
Canon Europe Ltd
European Patent Department
3 The Square
Stockley Park
Uxbridge, Middlesex UB11 1ET (GB)

(54) **ROBOT APPARATUS**

(57) A plurality of robot arms (201, 211, 301, 311) are each provided with indication devices (205, 215) that have indicators (205B, 215B) which indicate operability states of at least one other robot arm different from the robot arm on which the indication device is provided. Alternatively or in addition, the indication devices (205, 215) have indicators (205A, 215A) which indicate operability states of a respective robot arm upon which the indication devices are provided. Robot control devices (202, 212) which control operations of the robot arms communicate through a LAN (230) to share information regarding the states of the robot arms. Indication drive signals for the indication devices (205, 215) are generated based on states of servo control signals and/or brake control signals for the robot arms.

FIG. 1



EP 2 965 874 A2

Figure 2.D.8: Example of an AI patent document with highlighted keyword matches

(19) Europäisches Patentamt / European Patent Office / Office européen des brevets

(11) **EP 2 259 215 A1**

(12) **EUROPEAN PATENT APPLICATION**

(43) Date of publication:
08.12.2010 Bulletin 2010/49

(51) Int Cl.:
G06N 7/00 *(2006.01)* ***G06N 3/04*** *(2006.01)*

(21) Application number: **09175410.1**

(22) Date of filing: **09.11.2009**

(84) Designated Contracting States:
AT BE BG CH CY CZ DE DK EE ES FI FR GB GR HR HU IE IS IT LI LT LU LV MC MK MT NL NO PL PT RO SE SI SK SM TR
Designated Extension States:
AL BA RS

(30) Priority: **04.06.2009 EP 09161922**

(71) Applicant: **Honda Research Institute Europe GmbH**
63073 Offenbach/Main (DE)

(72) Inventor: **Knoblauch, Andreas**
63500 Seligenstadt (DE)

(74) Representative: **Rupp, Christian**
Mitscherlich & Partner
Patent- und Rechtsanwälte
Sonnenstrasse 33
80331 München (DE)

Remarks:
Amended claims in accordance with Rule 137(2) EPC.

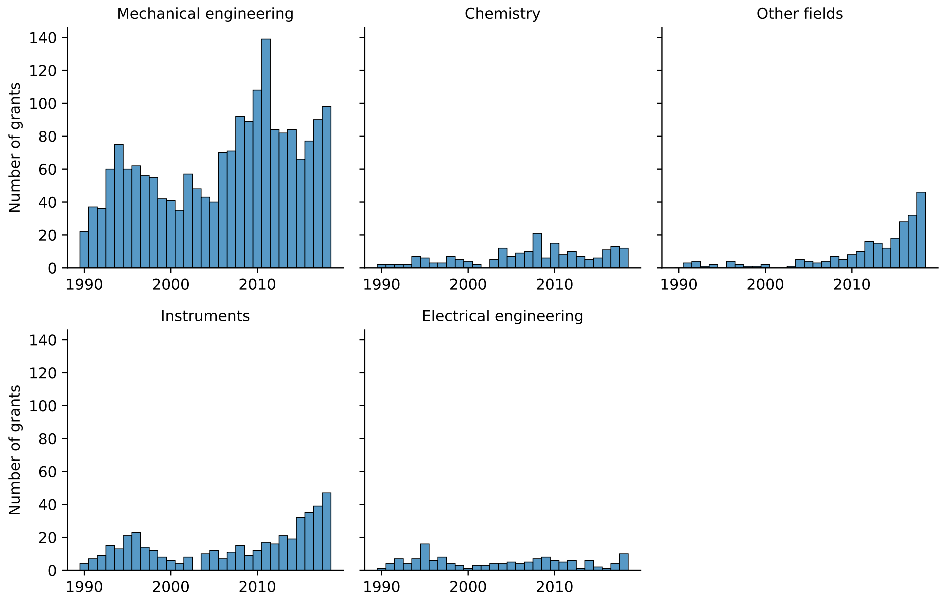
(54) **Method and structure for a neural associative memory based on optimal Bayesian learning**

(57) This invention is in the field of machine learning and neural associative memory. In particular the invention discloses a neural associative memory structure for storing and maintaining associations between memory address patterns and memory content patterns using a neural network, as well as methods for storing and retrieving such associations. Bayesian learning is applied to achieve non-linear learning.

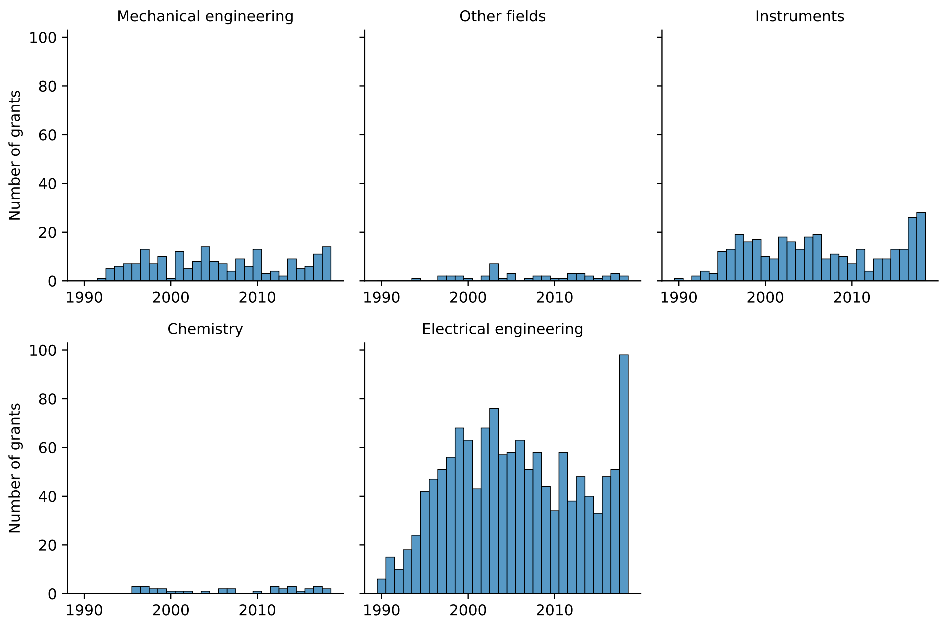
$$(u^1,v^1), (u^2,v^2), \ldots, (u^M,v^M) \longrightarrow \boxed{\text{AM}}$$

Fig. 1a

Figure 2.D.9: Evolution of Patents by Broad Technology Class



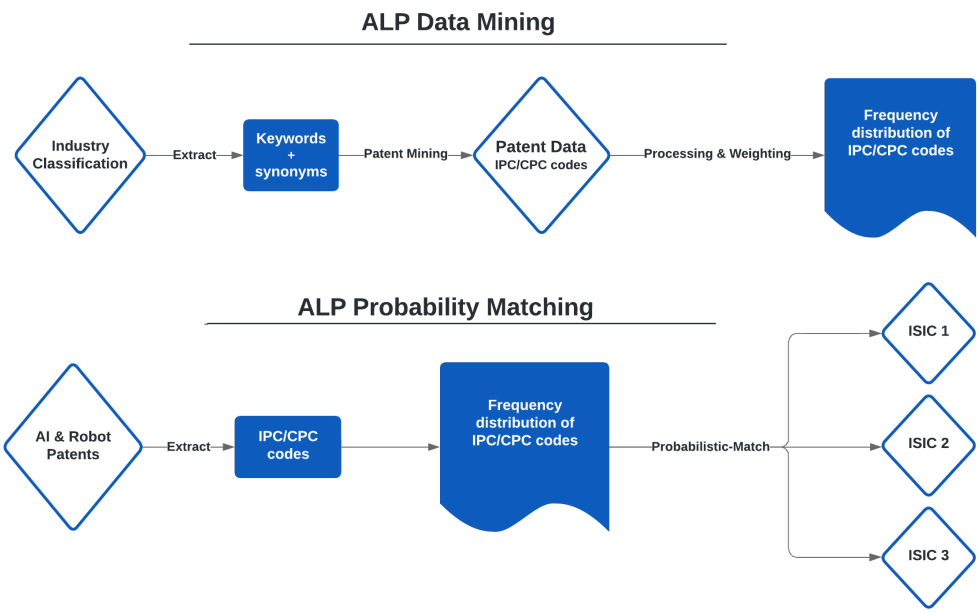
(a) Robotics Patents



(b) AI Patents

Notes: The figures show the number of patent grants in Robotics (Panel (A)) and AI (Panel (B)) in broad technology classes over time.

Figure 2.D.11: ALP process based on Lybbert & Zolas (2014). Author's own depiction.



Chapter 3

Artificial Intelligence and the Task Content of Occupations [1]

Artificial Intelligence (AI) has evolved rapidly and is now applicable in many domains. The public debate around AI oscillates between fascination with the new possibilities and fear of its potential dangers. In particular, there is a widespread concern that the diffusion of AI will sharply reduce the demand for labor.

An emerging literature has started to investigate the employment effects of AI (e.g., Acemoglu et al., 2022; Alekseeva et al., 2021; Brynjolfsson et al., 2018; Felten et al., 2018; Mann and Püttmann, 2023; Webb, 2020). Most of the literature finds few displacement effects and a limited impact on average wages. That does not mean, however, that AI has not left its mark on the labor market.

Yet, little is known about how AI reshapes the content of jobs. In particular, which skills actually lose importance, and which tasks become more important with AI? Moreover, we lack evidence on whether AI has an impact on worker careers beyond displacement. Given the broad applicability of AI, it is unclear whether earlier waves of technological change, in particular the diffusion of industrial robots, can provide any guidance on these questions.

[1] This chapter is joint work with Christina Gathmann and Erwin Winkler. We are grateful to Matias Cortes, Daniel Haanwinckel, Markus Nagler, Regina Riphahn, and participants at SOLE, University of Trier, University of Duisburg-Essen, KU Leuven, the AI conference, and several workshops for helpful comments and suggestions.

In the first part of the paper, we ask how AI has shifted the content of jobs and how this contrasts with the impact of robots. We use individual-level survey data (BIBB) to characterize the tasks performed on the job; the data have previously been used to analyze the accumulation of task human capital (Gathmann and Schönberg, 2010) and technological task changes over time (Spitz-Oener, 2006). The detailed nature of our task data allows us to track changes in tasks performed on the job within narrowly defined occupations and industries over more than a decade.

A key challenge is measuring the new technological opportunities of AI tools. We apply a novel measure, which uses Natural Language Processing on patent data from the European Patent Office to characterize the evolution of AI and, for comparison, robots (Gathmann and Grimm, 2023). AI shows features of a general-purpose technology as it has diffused into many more industries than robots, which are fairly concentrated in a few industries in manufacturing. Further, our patent-based measures of robot and AI exposure correlate closely with actual robot installations and jobs requiring AI skills posted in online job vacancies. Our new measures have two key advantages over previous indicators: First, our measures vary across detailed industries using the technologies and within industries over time to capture the evolving capabilities of AI and robots. Second, our measures quantify the exposure of industries to the capabilities of AI; we can use them to study their impact on the task content of jobs, independently of whether the change is related to automation, productivity enhancement, or the emergence of new work processes.

We then compare the job tasks of workers with similar demographics and working in the same detailed occupation and broad industry, thereby exploiting variation in AI exposure by detailed industry and over time. We compare our results to the task-changing impact of robots. The prior literature indicates that robots replace routine-intensive jobs and mostly affect low-skilled workers (e.g., Acemoglu and Restrepo, 2020; Webb, 2020; Dauth et al., 2021). If we find a similar result with the new patent-based measure of robotics technology, this serves as an important validity check for our approach. Moreover, there are possibly important interactions between the two technologies as AI tools can often be used to operate robots, for instance. Controlling for robot exposure is therefore important to tease out the partial effect of AI on the task content of jobs.

Our results show that AI has had a very different effect on the content of jobs than robots. We find that AI exposure decreases the share of non-routine tasks and increases the share of routine tasks that workers perform on their jobs. Zooming in, we find that AI mostly reduces non-routine analytical tasks related to gathering information, investigating, and documenting. In sharp contrast, robot exposure decreases routine tasks and increases non-routine tasks. A more detailed look reveals that robots mostly reduce routine tasks like monitoring machines and technical processes and producing goods, which appears in line with results in the literature on robots (e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021). Both technologies exhibit a differential dynamic over time: the effects of robots were strongest in the 2000s but phased out by 2018. We observe the opposite pattern for AI technologies: AI had few effects on job tasks in 2006, but its impact on job tasks has grown continuously over time. Interestingly, we find that AI-related changes in job tasks are strongest for low- and medium-educated workers and for older workers. Overall, these results are in line with the hypothesis that AI technologies, in contrast to robots, are substituting for non-routine tasks performed by workers.

In the second part of the paper, we turn to the question of how workers adapted to the observed task shifts. To study the reallocation of workers across firms, industries, and occupations in response to the changes initiated by AI, we match our task measures to administrative social security records of the labor market careers and earnings of workers in Germany. We find that AI exposure leads to a small decline in employment and earnings. The decrease in days employed is driven by employees moving between firms. In particular, we find that this mobility occurs mainly within broad (2-digit) industries, and employees tend to switch to firms in industries less exposed to AI, keeping their initial occupation. The increase in mobility associated with AI exposure is mainly driven by workers with a high share of analytical tasks. For robots, we find the opposite effect as employees exposed to robots experience increased job stability at the initial firm, consistent with prior evidence for Germany (Dauth et al., 2021).

In addition to a better understanding of the labor market impacts of AI, our paper contributes to at least three other strands of the literature. First, we make use of a new measure to identify the impact of AI on labor markets in Germany based on patent data. Our measure captures advances in AI technologies in using industries over several decades. Measuring progress in AI technologies is challenging. Previous attempts have produced cross-sectional measures at the occupational level of whether a task might be potentially automated by AI (Felten et al., 2018; Brynjolfsson et al., 2018; Tolan et al., 2021). We see three main advantages of our measure relative to the occupation-based measures: first, our measures do not impose assumptions about the automation potential. Second, our measures vary over time, thus allowing exposure to the knowledge frontier to evolve dynamically over time. Third, we can use our measures to study how the task content of jobs actually changes with AI and robots across but also within occupations. Arntz et al. (2017) demonstrate that expert assessments typically overstate automation potentials as they do not account for the heterogeneity and shifts in task usage within occupations. Firms might reshuffle the set of tasks performed in a job or add new tasks in response to the automation of some tasks. Likewise, workers may specialize in tasks that cannot be easily automated to avoid displacement.

An alternative approach has used the occurrence of AI skills in online job ads (Acemoglu et al., 2022; Alekseeva et al., 2021) or the growth of occupations with AI-related skills (Bonfiglioli et al., 2023) to proxy the adoption and diffusion of AI in firms. Most closely related to our measure are other patent measures on AI (Mann and Püttmann, 2023; Dechezleprêtre et al., 2020). Unlike them, we do not restrict our measure to automation patents but measure advances in AI technologies more broadly. Our patent-based measures of AI are strongly correlated with online job ads in using industries. Moreover, our measure for robots shows a strong correlation with the actual installation of robots in exposed industries.

By comparing the impact of AI to those of robots, we also contribute to a large recent literature studying the impact of industrial robots on the labor market (e.g., Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021; Koch et al., 2021; Humlum, 2019; Bonfiglioli et al., 2020). The literature has mostly focused on the impact on employment and wages as well as which workers adjust to the diffusion of robots. Our study is the first to analyze how robots affect detailed job tasks. In line with the view that robots are viewed as an automation technology, we show that it reduces the routine task share in occupations. Yet, it also increases the analytical task share with few displacement effects indicating that the replacement effect is largely offset by productivity gains. Moreover, we show that AI leads to reallocation across firms and industries, while robots actually reduce job mobility for the average worker. Finally, by analyzing the impact of robots and AI in parallel, we also capture the interaction between the two technologies, i.e. the fact that AI may enhance the capabilities of robots and reduce their costs.

Our paper builds on the task-based approach, which considers jobs and occupations as bundles of tasks, some of which are more prone to be substitutes or complements with technology than others (e.g., Autor et al., 2003; Acemoglu and Autor, 2011). It has been shown that routine-biased technological change has automated routine tasks (e.g., Autor et al., 2003; Spitz-Oener, 2006; Gregory et al., 2019) and replaced workers in the middle of the wage distribution leading to a polarization of jobs (e.g., Autor and Dorn, 2013; Goos et al., 2009; Cortes, 2016). While task changes typically occur both between *and* within occupations (Spitz-Oener, 2006; Atalay et al., 2018; Consoli et al., 2023, e.g.,), much of the existing literature on the link between technology and job tasks focuses exclusively on between-occupation changes in tasks. We contribute to this literature by connecting within-occupation task changes with measures for the technological advances in artificial intelligence and robots. Doing so provides new insights into the labor market effects of AI and stresses the importance of within-occupation adjustment processes for the debate around automation and technological unemployment. Our results suggest that a focus on between-occupation changes in tasks misses a substantial share of technology-induced task changes.

Finally, we contribute to the literature on the reallocation effects of technological change. Most of the literature has focused on adjustments to adopting automation technologies at the firm level (Bessen et al., 2019; Genz et al., 2021). While Bessen et al. (2019) find that incumbent workers are more likely to leave their employer after adoption, Genz et al. (2021) find that incumbent workers in adopting firms are less likely to leave the firm. We contribute to this strand by quantifying the effect of AI on those working in the exposed industry and distinguishing between reallocation across firms, industries, and occupations.

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 section 3.2, we explain how we measure tasks performed on the job and explain our empirical strategy for estimating the link between AI, robots, and tasks. In section 3.3, we present the results on the link between AI, robots, and task changes. In section 3.4, we analyze how workers adjust to the changes initiated by AI technologies. Finally, section 3.5 discusses the implications of our findings and concludes.

3.1 Measuring Advances in AI and Robotics

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 that all include 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 patent examiner.

We create a measure of advances in AI and robotics in three main steps. The first step is to classify patents as AI or robotics patents. 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 text inputs (see Gathmann and Grimm, 2023, for more details). We then perform a number of Natural Language Processing techniques, such as stemming, the removal of stop words, and tokenization, to prepare the text input for the keyword search. AI is often embedded in other inventions because algorithms and software are often not 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 a Natural Language Processing approach and classify AI patents based on keyword matches. This approach yields around 7000 AI patent applications and grants. Appendix Figure 3.A.2 shows that patent activity in AI has grown significantly in Europe since 2015. In addition to AI patents, we also identify patents in robotics which are mostly identified by the CPC code B25J9 'Programme-controlled manipulators'.

The second step is to identify the industries that make use of a patent in their production of goods or services. It is important to stress that we are not after the producers of patents ('innovators') but after firms in industries that potentially use the technological innovations protected by patents. Industries that produce a patent need not be the same as the industries using this 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 3-digit ISIC industry codes. 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 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 specific 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 producing 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 AI technologies that is available to firms for implementation in a given year. We therefore construct the following measures:

$$AI_{j(t-2)} = \sum_{s=1990}^{t-2} AIPatents_{is} \tag{3.1}$$

and likewise for robotics:

$$Robots_{j(t-2)} = \sum_{s=1990}^{t-2} RobPatents_{is} \tag{3.2}$$

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] We standardize both measures to have a mean of zero and a standard deviation of one to facilitate the interpretation of results. For each broad technology, the measure varies both by detailed industry (3-digit level) and over time.

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

[3]Weighting by forward patent citations to indicate the importance of an AI patent is not feasible given the recent nature of patent activity on AI.

3.2 AI and Tasks Performed on the Job

3.2.1 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 been used previously to analyze task changes over time (Spitz-Oener, 2006) and the impact of task distance on 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 restrict the sample to individuals aged 18-65 years, working full-time (at least 35 hours per week) in dependent employment. We drop self-employed individuals and civil servants.

To track how AI and robotics shift the task content of jobs, we focus on the three most recent waves of 2006, 2012, and 2018. We expect there to be little impact in 2006 but visible changes in the 2012 and 2018 waves [4]. The survey contains the socioeconomic background of the individual including educational background and age, but also the occupation and detailed industry.

Most importantly, we have detailed information on the tasks performed on the job. Specifically, the survey elicits whether an individual performs any of seventeen different tasks. We analyze the detailed tasks and aggregate them into four categories: routine tasks, non-routine analytical tasks, non-routine interactive tasks, and non-routine manual tasks. The individual tasks and their classification into the four 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 analytical tasks: Developing, researching or constructing; gathering

[4] A second reason we focus on the three latest waves is that there were major changes in the task-related questions between 1999 and 2006.

information, investigating or documenting; working with computer or tablet; organizing, planning or preparing work processes (of others).

Non-routine interactive tasks: 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 each individual task and the four broad task categories. For each task, we divide whether a task is performed frequently or occasionally by the total number of all tasks performed (frequently or occasionally). For the grouped task shares, we take the number of tasks that fall into category c divided by the total number of tasks performed :

$$TaskShare_{it}^{c} = \frac{\sum_{s \in c} Task_{ist}}{\sum_{s} Task_{ist}} * 100 \tag{3.3}$$

where i denotes the individual worker and s a task. $Task_{is}$ is equal to one if the individual performs task s frequently or occasionally; and zero otherwise. The task share can take 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 frequently or occasionally, and two of them fall into the routine manual category, then the routine manual task share equals 50%.

Appendix Table 3.B.1 shows descriptive statistics for the four task variables in each wave (2006, 2012, and 2018). Over the period from 2006 to 2018, the routine task share declined by 0.8 percentage points (Panel (a), esp. in the task of repairing. The analytical task share, in turn, sharply increased by 2.6 percentage points over the same time period (see Panel (a)), mostly driven by the organization and coordination of work processes (see Panel (b)).

3.2.2 Empirical Strategy

We investigate task changes on the job and the role that technological advances play in the observed task shifts. We first merge our patent-based exposure measures of advances in AI and robotics technologies to the individual worker sample by two-digit industry and period. We then estimate variants of the following model:

$$TaskShare^{c}_{ijot} = \beta_1 AI_{j(t-2)} + \beta_2 Robots_{j(t-2)} + X'_{it}\gamma + t_t + \lambda_j + \theta_o + \epsilon_{ijot} \quad (3.4)$$

where $TaskShare_{ijot}$ denotes the task share (routine, analytical, interactive, or manual) of worker i working in industry j and occupation o in survey year t (2006, 2012, or 2018) as defined in equation (3.3). Our main variables of interest are $AI_{j(t-2)}$ and $Robots_{j(\tau)}$, the cumulative number of AI or robot patents between 1990 and two years prior to the survey $(t-2)$ in using industry j.[5]

We include a number of demographic characteristics as control variables X_{it}: the education level (college degree, vocational or high school degree, and without a vocational or high school degree), five age groups (18-25, 26-35, 46-45, 46-55, 56-65), gender, German nationality. We further control for state fixed effects and wave dummies t_t. As the task content of jobs differs substantially between economic sectors, we control for 3 broad sectors (manufacturing, service, and primary sector) or, alternatively, 1-digit industries. All specifications use sample weights and cluster standard errors at the industry-year level.

3.2.3 Do Tasks Predict Future Exposure?

Rather than technological change shifting job tasks, growing specialization or outsourcing might actually shift the tasks performed in certain jobs, which in turn encourages firms to invest in automation or AI adoption. The shift in tasks would then be the cause rather than the consequence of exposure to AI in a job.

To address concerns about reverse causality, we run a balancing test to determine whether initial task shares (in 2006) help to predict future exposure to AI or robotics

[5]We use a time lag to allow for the technology to diffuse into the industry that uses it. The lag length does not make much difference, as shown in the robustness section below.

technologies. In Table 3.1, we regress our patent measures between 2006 and 2018 on task shares in 2006. Here, we exploit variations in AI and robot use across two-digit industries. Columns (1) and (3) show that task shares in 2006 do not predict future AI (column (1)) or robot (column (3)) exposure. The only exceptions are a positive correlation between the routine task share and robot patents and a negative correlation between the interactive task share and AI patents. Both of these coefficients are marginally statistically significant. In columns (2) and (4), we add indicators for broad economic sectors to account for the big differences in job tasks between agriculture, manufacturing, and services. Conditional on the main sector of activity, there is no meaningful relationship between initial task shares and future exposure to AI or robots. The F-test shown at the bottom of Table 3.1 highlights that the null hypothesis that all three coefficients are zero cannot be rejected at conventional significance levels. These estimates support our notion that job tasks cannot predict exposure to AI and robots within manufacturing and services.

Table 3.1: Balancing test

	AI Exposure (2006-18)		Robot Exposure (2006-18)	
	(1)	(2)	(3)	(4)
Routine tasks (2006) (%)	0.04	-0.02	0.08*	0.00
	(0.04)	(0.02)	(0.04)	(0.05)
Analytical tasks (2006) (%)	0.05	-0.00	0.04	-0.03
	(0.04)	(0.01)	(0.03)	(0.06)
Interactive tasks (2006) (%)	-0.04*	0.00	0.01	0.06
	(0.03)	(0.02)	(0.05)	(0.06)
Manufacturing sector		1.14		1.38*
		(0.82)		(0.74)
Primary sector		0.16		-0.02
		(0.20)		(0.21)
Adj. R^2	0.06	0.11	0.07	0.16
Obs.	56	56	56	56
P(Routine=Analytical=Interactive=0)	0.36	0.74	0.06	0.57

Note: Table reports industry-level regressions of the growth of AI patents between 2006 and 2018 (columns (1) and (2)) and of robot patents between 2006 and 2018 (columns 3 and 4) on task shares in 2006 and sector dummies. AI and robot patents are normalized to a mean of zero and a standard deviation of one. Regressions are weighted by the number of observations in the respective industry in 2006. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The last row shows the p-value of an F test with the null hypothesis that the coefficients of the routine, analytical, and interactive shares are jointly zero.

3.3 AI and Changes in Job Tasks

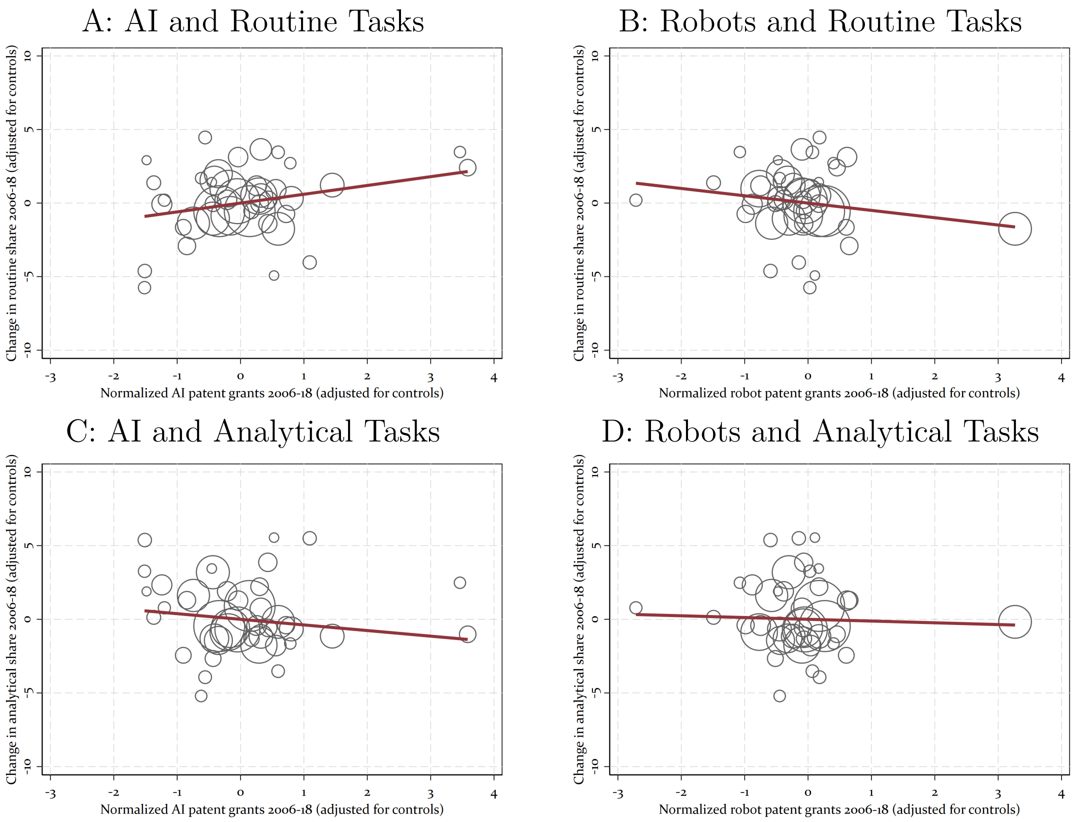
3.3.1 Industry-level Correlations

We start out with simple descriptive evidence relating changes in job tasks to our patent-based exposure measures at the industry level. Figure 3.1 plots the change in the routine task share between 2006 and 2018 against the number of AI and robot patents between 2006 and 2018. We first residualize both variables from demographics and sector.[6] Interestingly, Panel A suggests that AI technologies go along with an increase in the relative importance of routine tasks. This is in sharp contrast to the results for robot patents displayed in Panel B of Figure 3.1. Robots are associated with a decline in the routine task share – as expected from prior studies on robots (e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021; Webb, 2020). Panel C and D in Figure 3.1 show the relationship between analytical tasks, robots, and AI. We again find stark differences: AI technologies actually reduce analytical tasks, while there is little association for robots.

Appendix Figure 3.A.3 shows corresponding correlations for the group of interactive and manual tasks. Industries using AI technologies rely less on interactive tasks, while industries employing robots see an increasing need for interaction tasks. For manual tasks, the patterns are more muted: AI exhibits little relationship, while robots, in line with its potential for automating physical tasks, are associated with fewer manual tasks in an industry. These industry-level correlations provide a first hint that AI affects the task content of jobs in fundamentally different ways than robots.

[6]Demographic controls include the three education groups, five age groups, gender, and German nationality. Sector controls are manufacturing, services, and the primary sector.

Figure 3.1: AI, Robots, and Job Tasks



Note: The figure shows the relationship between changes in task shares between 2006 and 2018 and cumulative AI or robot patent-based knowledge after adjusting for demographics and sectors. Patent measures are the cumulative number of patents between 1990 and 2018 and are normalized to have a mean of 0 and a standard deviation of 1. Demographic controls include the share of three education groups, five age groups, gender, and workers with German nationality. Sector controls include the manufacturing, service, and primary sector. 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.

3.3.2 AI, Robots and Worker-level Tasks

We now turn to the worker level and estimate how exposure to AI and robots affects individual task shares performed on the job by estimating equation (3.4) controlling for socio-demographics, occupation (2-digit) and industry (1-digit) fixed effects as well as year and state dummies. We thus compare workers in exposed industries to individuals with similar socioeconomic characteristics, working in the same occupation and industry whose detailed industry is less or not exposed to the new technologies.

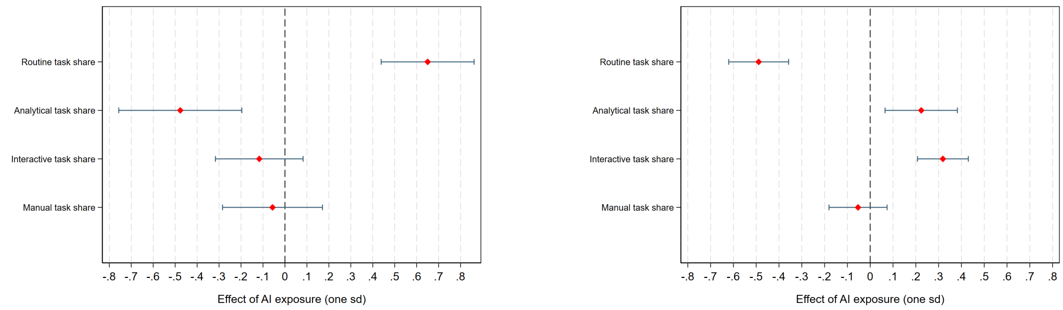
Figure 3.2 shows the impact of AI and robot exposure on the tasks performed by individual workers. Panel A shows that AI *increases* routine tasks of workers exposed to AI technologies relative to a worker of the same age, gender, education, occupation, and sector in a non-exposed industry. In line with the notion that robots mostly automate repetitive tasks, Panel B shows that the routine share declines for workers exposed to robot technologies.

In contrast, AI actually *decreases* analytical tasks, while robots tend to increase them. Moreover, robots also increase interactive tasks while we see little effect of AI on interactive tasks. Finally, there is no clear pattern of AI and robots on purely manual tasks. The individual worker level effects thus confirm the descriptive patterns at the industry level in Figure 3.1.

Table 3.2 demonstrates that these shifts occur across, but especially within occupations. The first specification controls only for socioeconomic characteristics and the broad sector in addition to state and year dummies (column (1)). We then zoom in on technology-induced task changes within occupations by adding occupation fixed effects at the 2-digit (column (2)) and 3-digit level (column (3)). The final specification is the one shown in figure 3.2 above, which includes 2-digit occupation and 1-digit industry fixed effects. In all specifications, we compare workers with similar observable characteristics working in the same broad sector where some are exposed to AI in their detailed industry while others are not.

Figure 3.2: Technology and Individual Job Tasks

A: AI and Job Tasks B: Robots and Job Tasks



Note: The figure shows point estimates and 95%-confidence intervals of a regression of task shares on AI and robot exposure, respectively. Controls include 3 education groups (university degree, vocational degree, less than vocational degree), gender, 5 age groups (18-25, 26-35, 36-45, 46-55, 56-65), a dummy for German nationality, 16 federal state dummies, dummies for manufacturing, service, and primary sector, year dummies, 2-digit occupation dummies, and 1-digit industry dummies. Number of observations: 38,480. Standard errors are clustered at industry-year level.

The table supports three key results: First, AI indeed reduces analytical tasks and increases routine tasks. Second, AI and robots have opposing effects on job tasks. Third, the observed task shifts with AI are strongest for individuals working in the same occupation. How important are the observed shifts in tasks? Between 2006 and 2018, the routine share declined by 0.81 percentage points in our data. The diffusion of robots would then account for a large share of this decline (60 percent). The diffusion of AI would actually largely offset this decline. Similarly, analytical task shares have overall increased by 1.43 percentage points between 2006 and 2018. Robots would contribute about 15 percent to this increase, while AI would have slowed down the growth in analytical tasks.

The observed shifts in aggregate task shares raise the question of which specific tasks change when AI is used in an industry. To investigate this, we use information on the seventeen detailed tasks available in the survey. We thus re-estimate equation (3.4) where we now have the probability of performing a detailed task as the dependent variable. The specification is otherwise the same as in column (4) of Table 3.2.

Figure 3.3 shows that within analytical tasks, AI mainly reduces the importance of gathering information, investigating, or documenting. As AI-assisted tools provide

Table 3.2: Technology and Individual Job Tasks

	(1)	(2)	(3)	(4)
Panel A: Routine tasks				
AI Exposure	0.44*	0.58***	0.35***	0.65***
	(0.24)	(0.10)	(0.10)	(0.11)
Robot Exposure	-0.60***	-0.47***	-0.41***	-0.49***
	(0.13)	(0.07)	(0.05)	(0.07)
R^2	0.20	0.36	0.39	0.36
Panel B: Analytical tasks				
AI Exposure	-0.33	-0.29**	-0.26**	-0.48***
	(0.41)	(0.12)	(0.10)	(0.14)
Robot Exposure	0.27	0.15**	0.10	0.22***
	(0.19)	(0.08)	(0.06)	(0.08)
R^2	0.15	0.37	0.40	0.38
Panel C: Interactive tasks				
AI Exposure	0.08	-0.11	-0.13	-0.12
	(0.19)	(0.10)	(0.09)	(0.10)
Robot Exposure	0.28***	0.31***	0.37***	0.32***
	(0.11)	(0.06)	(0.06)	(0.06)
R^2	0.15	0.32	0.34	0.32
Panel D: Manual tasks				
AI Exposure	-0.20	-0.18	0.03	-0.06
	(0.32)	(0.12)	(0.11)	(0.12)
Robot Exposure	0.04	0.01	-0.06	-0.05
	(0.16)	(0.06)	(0.06)	(0.07)
R^2	0.12	0.35	0.39	0.36
Demographic controls	X	X	X	X
State dummies	X	X	X	X
Year dummies	X	X	X	X
Sector dummies	X	X	X	
2-digit occupation dummies		X		X
3-digit occupation dummies			X	
1-digit industry dummies				X

Note: Number of observations: 38,480. Sum of patents from 1990 through t-2 normalized to have mean of 0 and standard deviation of 1. Task shares in year t are measured in percent. Demographic controls include 3 education groups (university degree, vocational degree, less than vocation degree), gender, 5 age groups (18-25, 26-35, 36-45, 46-55, 56-65), a dummy for German nationality, and 16 federal state dummies. Sector controls include dummies for manufacturing, service, and primary sector. Regressions employ sample weights. Standard errors clustered at industry-year level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

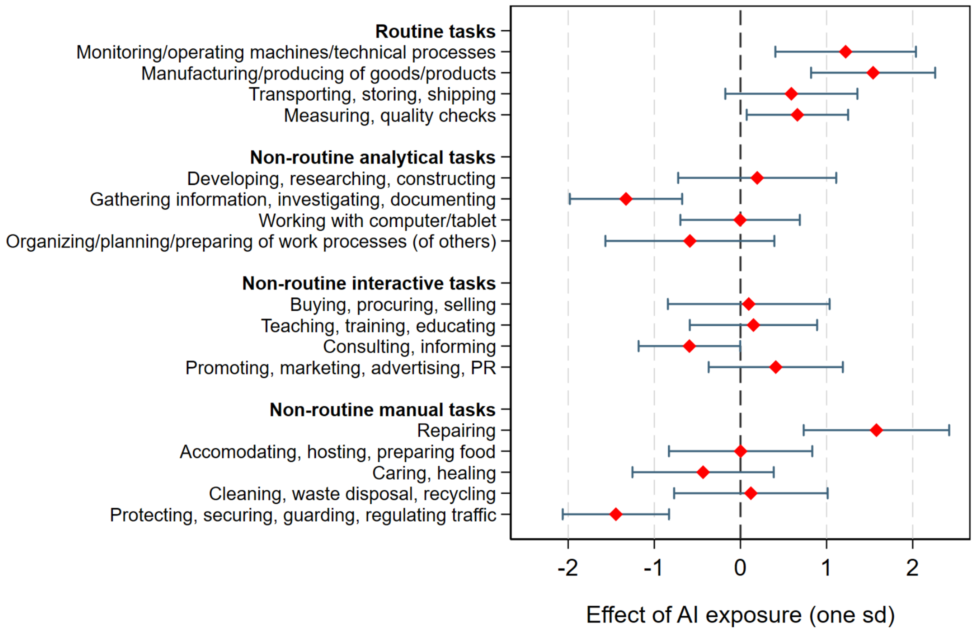
information, they reduce the need to collect and gather information elsewhere. One example would be a malfunctioning machine where AI can diagnose and possibly repair the problem, whereas before, the responsible person had to call the service provider or study a handbook to fix the machine. There are few changes in other non-routine analytical tasks like working with a computer or tablet or developing, researching and constructing. AI does not replace the need to use a computer, and most people using AI have worked with a computer or tablet at their jobs before.

We also found the surprising result that AI increases the routine task share. Here, Figure 3.3 shows that AI requires more time for monitoring or operating machines and technical processes, as well as performing quality checks. We call these 'high-level' routine tasks and distinguish them from standard routine tasks. The standard notion of routine tasks is that they can be easily codified into rules and eventually taken over by a machine. An example would be a repetitive task that a worker used to perform in an assembly line, for instance. AI, in contrast, needs humans to evaluate the process and output of the algorithms. AI will require more workers to perform such high-level tasks in the future.

Figure 3.3 further shows few effects of AI on interactive tasks but opposing effects on manual tasks. AI technologies reduce the relative importance of protecting, securing, guarding, and regulating traffic but seem to increase the time spent on repairing and fixing things. AI, when built into tools like cameras or other image recognition tools, can take over some tasks in securing and guarding buildings or production processes and report issues when problems arise. Yet, human labor is needed to step in when things go wrong, and AI cannot solve a problem or a problem with the AI tool itself emerges.

The results for detailed job tasks again demonstrate how different the impacts of robots and AI are on jobs and workplaces. Figure 3.4 shows the results from the coefficient for robot exposure for the detailed job tasks. Robots reduce the need for several routine tasks like monitoring machines or technical processes, producing goods and services, as well as measuring and performing quality checks or technical processes. Many of these activities, esp. in manufacturing, can be

Figure 3.3: AI and Detailed Job Tasks

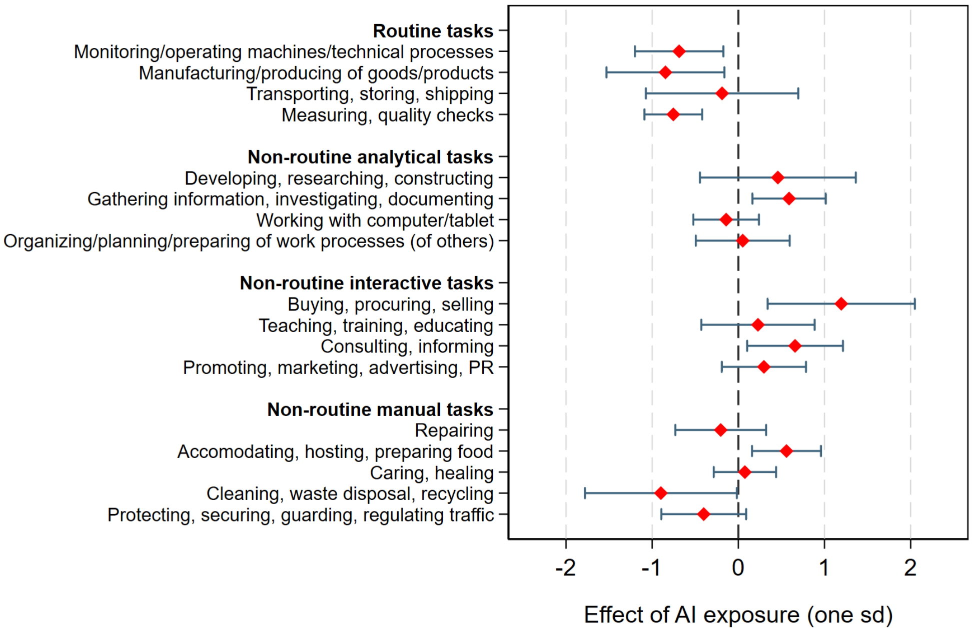


Note: The figure shows the link between AI patents and the probability of performing a single task. The dependent variable is a dummy variable (multiplied by 100). Regressions include demographic controls (3 education groups (university degree, vocational degree, less than vocation degree), gender, 5 age groups (18-25, 26-35, 36-45, 46-55, 56-65), a dummy for German nationality), year dummies (2006, 2012, 2018), 2-digit occupation dummies, and 1-digit industry dummies. Regressions employ sample weights. Standard errors clustered at industry-year level. The lines reflect 95% confidence intervals.

performed more and more by robots themselves. Yet, robots increase the need for analytical tasks involving creative work like researching and developing, gathering information, or documenting. Robots also increase interactive tasks like consulting and informing, but also customer and client relationships in sales or procurement, in which humans (still) have a comparative advantage.

The development of AI has dramatically accelerated in recent years, which is reflected in the fact that AI patents accelerated in Europe after 2015 (see Appendix figure 3.A.2). As such, we would expect the impact of AI on job tasks to become stronger over time. To investigate this, we run separate estimations for 2006 and 2018.

Figure 3.4: Robots and Detailed Job Tasks



Note: The figure shows the link between robot patents and the probability of performing a single task. The dependent variable is a dummy variable (multiplied by 100). Regressions include demographic controls (3 education groups (university degree, vocational degree, less than vocation degree), gender, 5 age groups (18-25, 26-35, 36-45, 46-55, 56-65), a dummy for German nationality), state dummies, year dummies (2006, 2012, 2018), 2-digit occupation dummies, and 1-digit industry dummies. Regressions employ sample weights. Standard errors clustered at industry-year level. the lines reflect 95% confidence intervals.

Table 3.3 shows that AI had little effect on job tasks in 2006. In contrast, we see that the automating force of robots reduced both routine and manual tasks in 2006. By 2018, the situation had shifted: AI began to replace analytical tasks and increased the need for some more routine tasks within occupations. Robots, in turn, still reduce routine tasks but, by 2018, have no impact on manual tasks. These results are in line with other studies in which the impact of robots was strongest in the 2000s, while AI has just started to affect the labor market very recently.

3.3.3 Heterogeneity by Skill and Age

The average effects of AI on job tasks may hide substantial heterogeneities across workers. Technological change is rarely skill-neutral. The diffusion of computers and related technologies have been strongly skill-biased in favor of more educated

Table 3.3: Comparing the Effects across Time

	2006		2012		2018	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Routine tasks						
AI Exposure	-0.03	0.46	0.48***	0.69***	0.41***	0.73***
	(0.30)	(0.33)	(0.14)	(0.18)	(0.15)	(0.16)
Robot Exposure	-0.42*	-0.56*	-0.48***	-0.49***	-0.42***	-0.52***
	(0.23)	(0.29)	(0.07)	(0.14)	(0.06)	(0.06)
R^2	0.39	0.36	0.40	0.38	0.40	0.37
Panel B: Analytical tasks						
	2006		2012		2018	
AI Exposure	-0.41	-0.65*	-0.20	-0.33	-0.28*	-0.57***
	(0.26)	(0.37)	(0.20)	(0.27)	(0.15)	(0.18)
Robot Exposure	0.49*	0.70**	-0.05	0.07	0.10	0.25***
	(0.25)	(0.30)	(0.12)	(0.19)	(0.06)	(0.07)
R^2	0.42	0.39	0.40	0.37	0.41	0.38
Panel C: Interactive tasks						
	2006		2012		2018	
AI Exposure	0.33	0.28	-0.35**	-0.27	-0.12	-0.14
	(0.22)	(0.21)	(0.16)	(0.19)	(0.10)	(0.09)
Robot Exposure	0.49***	0.39**	0.52***	0.40***	0.32***	0.30***
	(0.17)	(0.15)	(0.08)	(0.10)	(0.05)	(0.04)
R^2	0.36	0.33	0.37	0.35	0.33	0.31
Panel D: Manual tasks						
	2006		2012		2018	
AI Exposure	0.11	-0.10	0.06	-0.10	-0.00	-0.01
	(0.13)	(0.21)	(0.22)	(0.30)	(0.16)	(0.09)
Robot Exposure	-0.56***	-0.52***	0.01	0.02	-0.00	-0.02
	(0.12)	(0.16)	(0.12)	(0.16)	(0.08)	(0.06)
R^2	0.39	0.36	0.41	0.37	0.42	0.37
Demographic controls	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Sector FE	X	X	X	X	X	
Occupation FE (2-dig)		X		X		X
Occupation FE (3-dig)	X		X		X	
Industry FE (1-dig)		X		X		X

Note: Number of observations: 37,202. Sum of patents from 1990 through t-2 normalized to have mean of 0 and standard deviation of 1. Task shares in year t are measured in percent (0-100). Sector controls include dummies for manufacturing, service, and primary sector. Time controls include dummies for survey years (t) 2006, 2012, 2018. Demographic controls include 3 education groups (university degree, vocational degree, less than vocation degree), gender, 5 age groups (18-25, 26-35, 36-45, 46-55, 56-65), a dummy for German nationality, and 16 federal state dummies. Regressions employ sample weights. Standard errors clustered at 2-digit industry-year level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

workers (see, e.g. Autor et al., 2003), for instance. Robots mainly seemed to have automated tasks of low-skilled workers. Is this also true for AI? Some authors have argued that AI might automate tasks that are typically performed by more educated workers (see, e.g., Agrawal et al., 2019). Yet, AI might also complement tasks performed by more skilled workers, thereby increasing their productivity (Felten et al., 2019; Agrawal et al., 2019).

We investigate whether AI affects the job content of high-skilled workers, i.e. those with a college degree, differently than less-skilled workers without a college degree.[7] We re-estimate equation (3.4) where we add an interaction effect between AI and whether a worker is highly skilled or not. Table 3.4 shows that the increase in routine and the decline in analytical tasks occur mostly for less skilled workers. High-skilled workers, in turn, see no change in the composition of their job tasks.

Technological change might also affect workers of different ages. Technologies might make some skills obsolete, which should affect older workers more. Yet, older workers also have more secure jobs, which might shield them from the disruptive impact of new technologies. In that case, younger workers might have to adjust more than older workers. It is also often argued that younger workers are more flexible in adapting to new technologies, possibly because they are more acquainted with the skills to use them. In the case of robots, it seemed that, indeed, younger workers had to shoulder most of the costs of adjustment (Dauth et al., 2021).

We again allow for interaction effects between the exposure to AI and the age of the worker. Interestingly, Appendix Table 3.B.2 shows few differences in task shifts related to AI between younger and older workers. AI slightly increases the interactive task shares for younger workers, while the task shares remain unchanged for middle-aged workers and slightly decrease for workers above 35 years of age.

[7] We combine low- and medium-skilled workers as those without a vocational degree make up only 5% in our sample.

Table 3.4: Heterogeneity by Skill

	Routine task share		Analytical task share	
	(1)	(2)	(3)	(4)
AI	0.46***	0.76***	-0.34***	-0.54***
	(0.11)	(0.13)	(0.12)	(0.17)
AI x High-skilled	-0.58**	-0.64*	0.44	0.39
	(0.29)	(0.36)	(0.35)	(0.42)
R^2	0.39	0.37	0.40	0.38
	Interactive task share		**Manual task share**	
AI Exposure	-0.15*	-0.15	0.03	-0.07
	(0.09)	(0.10)	(0.13)	(0.14)
AI x High-skilled	0.12	0.17	0.03	0.08
	(0.23)	(0.23)	(0.23)	(0.25)
R^2	0.34	0.32	0.39	0.36
Demographic controls	X	X	X	X
State FE	X	X	X	X
Year FE	X	X	X	X
Sector FE	X	X	X	X
Occupation FE (2-dig)		X		X
Occupation FE (3-dig)	X		X	
Industry FE (1-dig)		X		X

Note: Number of observations: 37,202. The dependent variables are task shares of individual i working in occupation o and industry j in year t measured in percent (0-100). The key independent variables are the cumulative number of AI patents from 1990 to 2018 standardized to have mean zero and standard deviation of one; and an interaction effect with the highest educational degree of the worker. Sector controls include dummies for manufacturing, service, and primary sector. Time controls include dummies for survey years (t) 2006, 2012, 2018. Demographic controls include 3 education groups (university degree, vocational degree, less than vocation degree), gender, 5 age groups (18-25, 26-35, 36-45, 46-55, 56-65), a dummy for German nationality, and 16 federal state dummies. Regressions employ sample weights. Standard errors clustered at 2-digit industry-year level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

3.3.4 Robustness Checks

Table 3.B.3 reports several robustness checks focusing on the impact on routine (panels A and B) and analytical tasks (panels C and D). Our patent measure for AI activity includes patents by German inventors. In firms that produce and use

a patent, industry-level demand shocks might, therefore, shift job tasks but also innovation activity. Likewise, a supply shock, like a shortage of engineers, for instance, might shift both the content of jobs and the potential to innovate and patent. To address these concerns, we drop all patents filed by inventors residing in Germany. The resulting measure of AI and robotics is then based solely on patents invented outside of Germany. As shown in columns (1) and (2) of panels A and C in table 3.B.3, the exclusion of German patents does not change our results.

One might worry that our results are sensitive to the particular construction of the AI measure. Instead of the standardized sum of patents, we use the absolute number of patents (columns (3) and (4)) or the log transformation (columns (5) and (6) in panels A and C of table 3.B.3. We find qualitatively similar effects on the routine task share. The positive effect of AI and the negative effect of robots on routine tasks persists. The same holds true for the analytical task share, where our robustness analysis largely confirms the same patterns found in the original specification. The only exception is the coefficient on the analytical task share loses statistical significance in the log specification with 3-digit occupation dummies.

Similarly, one might be concerned that the time lag between the patent grant and the actual implementation of the new technology in firms is longer than the two years we use in our main specification. Columns (1) and (2) of Panels B and D in table 3.B.3 show that our results are very similar if we allow for a five-year lag instead.

AI technologies may also affect how often a task is performed on the job. We use two alternative definitions of our dependent variables to test for the importance of the intensive margin. The first one codes the task variable in three categories: zero if a task is not performed, one if it is performed occasionally, and two if it is performed frequently. Columns (3) and (4) of Panels B and D in table 3.B.3 show that the results are virtually unchanged if we exploit the intensive margin of task usage.

The second alternative measure looks at the sub-sample of workers who report performing a given task and tests whether some tasks are more frequently performed because of AI. Interestingly, the coefficients show a similar impact on the intensive margin than overall (see columns (5) and (6) of Panels B and D in table 3.B.3), which suggests that AI shifts job tasks both at the extensive margin (more workers use routine tasks than before) and the intensive margin (more workers perform routine tasks more frequently). Overall, the results are very robust to alternative definitions of the task and patent measures or the (potential) endogeneity of patents granted to German inventors.

3.4 AI and Job Reallocation

Our findings thus far show that AI has changed the task content of jobs for workers. These effects are typically strongest within detailed occupations. Yet, how do these observed shifts in job tasks impact the labor market careers of workers?

The task changes we document could occur through several channels. The first channel works only through actual changes in the task content of jobs with no impact on the composition of workers holding the jobs. We call this the with-job adjustment. A second channel would work through the displacement of workers in jobs with automated tasks. A third channel of adjustment would see workers switching employers and possibly industries or occupations to reduce their exposure to the new technologies or to take advantage of new opportunities.

The implications of the three adjustment channels are very different. If the first channel dominates, policymakers do not need to worry about large-scale job losses or the costs of sectoral or occupational reallocation. Yet, employers need to worry about how to adapt the skills of their workforce to adapt to the new tasks required on the job. In the second scenario, the costs of adaptation are primarily borne by those who get displaced. Policies might then need to focus more on upskilling and re-employing displaced workers. In the third scenario, most of the adjustment occurs through reallocation across firms, industries, or occupations. These might lead to losses of human capital but also possibly gains by moving to better-paying firms, for instance. Policy-makers might then provide incentives for reallocation or job search assistance to identify good job opportunities, for instance.

3.4.1 Administrative Labor Market Data

To study how workers adjust to the new technologies, we turn to administrative data from the social security records. The 'Sample of Integrated Labour Market Biographies' (SIAB) is a 2% random sample of the administrative social security records, which cover about 80% of the German workforce, excluding self-employed, civil servants, and military personnel. We know the individual's employment status, i.e., whether the person is employed, registered as unemployed, or non-employed; we further have detailed information on the education, occupation, age, gender, nationality, as well as the daily wage earned. We further have some information on the establishment, such as the detailed industry, location, establishment size, and the composition of its workforce.

Starting from an annual panel, we aggregate the data into three broad periods: 2004-2009, 2010-2015, and 2016-2021. The periods cover the years around the survey waves 2006, 2012, and 2018, for which we analyzed the task changes above. We then merge our patent-based measure of AI and robotics technologies to the administrative data using the 3-digit industry and period as described in more detail in the next section.

3.4.2 Empirical Strategy

We estimate variants of the following specification:

$$Y_{ijot} = \beta^{AI} AI_{jt} + \beta^{Rob} Rob_{jt} + \theta_o + \delta_t + \mu_j + \gamma X_{it} + \epsilon_{ijot} \tag{3.5}$$

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

AI_{jt} and Rob_{jt} denote the AI and robot patent exposure in 3-digit industry j in period t. The measures are calculated as the cumulative number of AI and robot patents from 1990 to 2006, 2012, or 2018. Patent measures are standardized to have a mean of zero and a standard deviation of one.

All control variables in equation (3.5) are measured in the first year of the period (i.e., 2004, 2010, or 2016), which we denote as the base year. The control variables include dummies for workers' 2-digit occupation (θ_o), 1-digit industry (μ_j), and time period (δ_t). We further include a number of base-year controls X_{it} at the worker, job, and firm level. More specifically, it includes the worker's education level (university degree, vocational degree, or low-skilled), gender, five age groups (18-25, 26-35, 36-45, 46-55), a dummy for foreign nationality, log base year earnings, 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.

Equation (3.5) then compares workers with similar demographics and labor market history who are initially employed in the same 2-digit occupation, 1-digit industry, and region. The estimation then exploits variation in AI and robot exposure between 3-digit industries and within 3-digit industries over time to identify the impact of exposure to AI on employment, earnings, and worker mobility during the following years. Standard errors are clustered at the 3-digit industry x period level.

3.4.3 Impact on Employment and Earnings

To assess the importance of the displacement effect, we first study the impact of AI on employment and earnings of individual workers. The outcomes of interest are cumulative employment and (log) earnings during the five-year period. Table 3.5 shows that workers who are more exposed to AI have lower employment and earnings over the period than comparable workers in less exposed industries. The effect is modest, however: a one standard deviation increase in AI exposure would decrease employment by 0.25% and earnings by 0.27% based on the estimates in columns (2) and (4), respectively.

These results suggest that most of the adjustment to the new technologies does – at least for now – *not* work through the displacement of workers or a decline in earnings.

Table 3.5: AI, Robots, Employment, and Earnings

	Days employed (in logs)		Earnings (in logs)	
	(1)	(2)	(3)	(4)
AI Exposure	-0.26***	-0.25***	-0.21*	-0.27**
	(0.09)	(0.08)	(0.12)	(0.12))
Robot Exposure	0.22	0.23	0.39	0.51
	(0.15)	(0.15)	(0.37)	(0.38)
Mean Y	735.03	735.03	1188.08	1188.08
R^2	0.06	0.06	0.58	0.58
Obs.	1,208,656	1,208,656	1,228,567	1,228,567
Occupation FE	No	Yes	No	Yes

Note: All columns control for period, demographics, log base year earnings, state, tenure, firm size, and 1-digit industry. Standard errors are clustered at the 3-digit industry x period level.

3.4.4 Worker Reallocation

Rather than through displacement, the reorganization of production processes and work processes in firms might require some workers to move firms, industries, or occupations. Yet, firms adopting AI may also need new workers to help implement or make productive use of the new technology.

Table 3.6 analyzes whether AI (and robot) exposure leads to more or less reallocation of labor. Our dependent variables are now whether an individual moves employers, the industry of employment, and or occupation during the period, between the base year and one of the years within the period.

Column (1) of table 3.6 shows that exposure to AI induces more workers to switch employers. In line with the previous literature (Dauth et al., 2021), we find that robots actually reduce worker mobility across firms. The point estimate points to a modest effect: a one standard deviation increase in AI exposure raises the probability of moving to a different firm by 0.63 percentage points.

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 turn to sectoral mobility between 3-digit and 2-digit industries. Column (3) of table 3.6 shows that robots not only reduce firm mobility, but also sectoral mobility. In contrast, AI has only a modest but not statistically significant effect on switching one's 3-digit industry. The next two columns investigate whether workers are more likely to switch jobs within or between their initial 2-digit industry. Column (5) shows that most of the job switches shown in column (1) occur within the same 2-digit industry. Job reallocation might occur from non-adopting firms to adopting firms within exposed industries or between industries that are more or less exposed to AI technologies. The results in columns (3) to (5) imply that AI induces workers to leave their initial industry. The question then is whether individuals are primarily leaving exposed industries or whether there is churning where some workers leave industries exposed to AI, and others enter to take advantage of new job opportunities. Column (6) investigates this using an indicator of whether the industry switch is to a less exposed industry or not. The estimate is positive, indicating that worker mobility occurs primarily away from industries that are exposed to AI and into industries that are less or not exposed to AI. Hence, more workers seem to move away from firms exposed to AI technology, thus reducing employment in exposed industries.

Overall, the results in tables 3.5 and 3.6 show that adjustments to AI exposure occur both through some displacement of workers and workers switching out of exposed industries into non-exposed industries. Job and sectoral mobility, in addition to some modest displacement, is thus one important adjustment mechanism to emerging AI technologies. In contrast, we find little evidence that AI exposure increases occupational mobility. Most of the adjustment to the new technologies thus seems to occur through changes in job tasks within the same occupation. Individuals working in exposed industries see their job content change, while individuals in the same occupation in non-exposed industries do not see such adjustments.

It is important to stress again the substantial differences in how AI and robots affect jobs and worker careers. Robots have little displacement effect. Moreover, robots reduce mobility as employees are more likely to stay with their employer;

workers are even more likely to remain in their current industry. This result is in line with Dauth et al. (2021), who show that robot exposure is associated with increased job stability at the initial employer using a different technology measure for manufacturing. Thus, adjustment to robots seems to work largely through changes in the job content of incumbent workers.

Table 3.6: AI, Robots and Worker Reallocation

	Δ Firm (1)	Δ Occupation (2)	Different Industry (3-dig) (3)	Different Industry (2-dig) (4)	Same Industry (2-dig) (5)	Lower AI Exposure (6)
AI Exposure	0.63**	-0.13	0.42	0.10	0.53*	1.62***
	(0.28)	(0.32)	(0.33)	(0.21)	(0.29)	(0.41)
Robot Exposure	-1.09***	-0.50	-1.21***	-1.16***	0.07	0.53
	(0.23)	(0.79)	(0.22)	(0.21)	(0.20)	(0.33)
Mean Y	35.61	30.11	23.87	21.44	14.17	8.16
R^2	0.13	0.16	0.11	0.11	0.04	0.06
Obs.	1,202,213	1,202,213	1,202,213	1,202,213	1,202,213	1,202,213

Note: All columns control for time window, demographics, log base year earnings, state, tenure, firm size, and 1-digit industries. SEs clustered at 3-digit industry x year level.

3.4.5 Differences between Occupations

We next investigate in which occupations AI exposure leads to the displacement and reallocation of workers. We use the average share for routine and analytical tasks from our survey data to characterize occupations as highly analytical and mostly routine (using a median split). We merge these task shares with our administrative data on workers at the 2-digit occupation and period level. We then interact our AI exposure measure with an indicator of whether an occupation is routine or analytical. Panel A of table 3.7 suggests that the displacement and reallocation of workers across firms and industries is stronger in low-routine occupations. Panel B shows that workers with a high analytical task content are much more likely to switch employers and industries than workers in occupations with a low analytical task share.

Is the reallocation of workers with low routine or high analytical task shares beneficial for the worker? Here, we focus on whether workers move to better-paying firms if they switch employers. We capture better-paying firms by AKM fixed effects (Abowd et al., 1999), which capture unobservable differences across firms like management quality, efficiency, or market position that lead to higher or lower wages (holding the composition of the workforce constant along observables).

Column (4) of table 3.7 shows two interesting patterns: first, Panel A indicates that workers in low-routine occupations are more likely to switch to better-paying firms when exposed to AI in their industry. Hence, the reallocation effect in response to AI seems to benefit some workers initially employed in occupations with a low routine share – partially offsetting the displacement observed in column (1) of Panel A. Second, workers initially employed in occupations with a high analytical share also seem to benefit from their higher mobility (see Panel B). Most of those workers are able to switch to better-paying employers (see column (4) of Panel B). Our survey evidence showed that AI decreases the demand for analytical tasks. Workers who were initially employed in highly analytical occupations respond to this declining demand by switching employers and industries – and benefit mostly from it as their skills are in high demand elsewhere. In contrast, our task data showed that AI increased the need for high-level routine tasks. This shift, in turn, induces workers initially employed in low-routine occupations to switch jobs and industries. Some workers benefit from this move as they are able to find a job at a better-paying firm.

3.4.6 Heterogeneity by Skill and Age

The reallocation of workers across industries raises the question of which employees actually adjust. We first investigate whether displacement and reallocation effects differ across high- and low-skilled workers and between workers of different ages.

We thus interact our AI exposure variable with dummies for college education and age dummies for the age groups 26 to 35 and older than 35. Panel A of table 3.8 shows that displacement effects are concentrated among less-skilled workers (column (1)). Moreover, less-skilled workers (and, to a lesser extent, high-skilled workers) are more likely to switch employers when exposed to AI (column (2)). High-skilled workers are also more likely to switch to a different industry (column (3)). We find no evidence that less- or high-skilled workers are more likely to move to better-paying firms (as measured by the firm's AKM effect).

Table 3.7: AI, Robots and Reallocation by Task Intensity

	(Log) Days Employed	Δ Firm	Δ Industry (3-dig)	Higher AKM Firm
	(1)	(2)	(3)	(4)
	Panel A: Routine task intensity			
AI Exposure	-0.27**	0.96***	0.60*	0.34***
	(0.11)	(0.33)	(0.36)	(0.12)
AI x Routine	0.05	-0.62**	-0.33	-0.51**
	(0.12)	(0.28)	(0.26)	(0.22)
	Panel B: Analytical task intensity			
AI Exposure	-0.05	0.07	-0.89**	-0.43*
	(0.16)	(0.35)	(0.43)	(0.22)
AI x Analytical	-0.23	0.66*	1.55***	0.58**
	(0.15)	(0.36)	(0.40)	(0.23)

Note: All columns control for time window, demographics, log base year earnings, state, tenure, firm size, and 1-digit industries. High routine (analytical) is a dummy which equals one if the routine (analytical) task share of the base-year 2-digit occupation is above the median and zero otherwise. SEs clustered at 3-digit industry x year level.

Overall, the results by education indicate that less-skilled workers witness not only a stronger change in their job content but are also more affected by displacement and less job stability. High-skilled workers, in contrast, have thus far witnessed few changes in their job and no displacement effects.

Panel B of table 3.8 reports the results for different age groups. While we saw no differential changes in the job content between younger and older workers, we do see substantial differences in displacement and reallocation effects across age groups. Workers older than 35 years of age see some displacement effects and are also more likely to switch employers and industries. For younger workers, we see no displacement effects but some reallocation for workers between the ages of 26 and 35. Most interestingly, workers who switch jobs quite often end up at higher-paying firms, and this effect is strongest for those above 35 years of age.

Again, these adjustment patterns to AI differ from those reported for robots, where it was young workers who have borne most of the adjustment costs, while older workers actually saw their employment stability increase (Dauth et al., 2021).

Table 3.8: Heterogeneity by Skill and Age

	(Log) Days Employed (1)	Δ Firm (2)	Δ (3-dig) Industry (3)	Higher AKM Firm (4)
		Panel A: Education		
AI Exposure	-0.26**	0.51**	0.22	0.01
	(0.11)	(0.26)	(0.33)	(0.08)
AI x High-skilled	0.03	0.29	0.50***	0.12
	(0.12)	(0.21)	(0.19)	(0.11)
		Panel B: Age		
AI Exposure	0.08	-0.90*	-0.91	-1.17***
	(0.21)	(0.48)	(0.60)	(0.41)
AI x Ages 26-35	0.23	1.01***	1.03***	0.90***
	(0.22)	(0.27)	(0.27)	(0.28)
AI x Ages >35	-0.53**	1.82***	1.52***	1.41***
	(0.27)	(0.49)	(0.47)	(0.45)

Note: All columns control for time window, demographics, log base year earnings, state, tenure, firm size, and 1-digit industries. SEs clustered at 3-digit industry x year level.

3.5 Conclusion

We have shown in this paper that AI has already shifted the task content of jobs. Using a new measure of exposure to AI and robot technologies based on patent data, we find that AI has decreased the analytical task share in jobs and increased the need for high-level routine tasks. The impacts on job tasks differ from those of robots, which have increased the demand for analytical tasks and reduced the demand for routine tasks. This observation challenges the hypothesis that AI would continue the trend of previous technologies to predominantly automate routine tasks, suggesting instead that AI is capable of performing non-routine tasks or turning them into more standardized processes. Most of the changes occur within detailed occupations. We also show that the effects of AI on job tasks are more pronounced for less-skilled workers and have been growing over time.

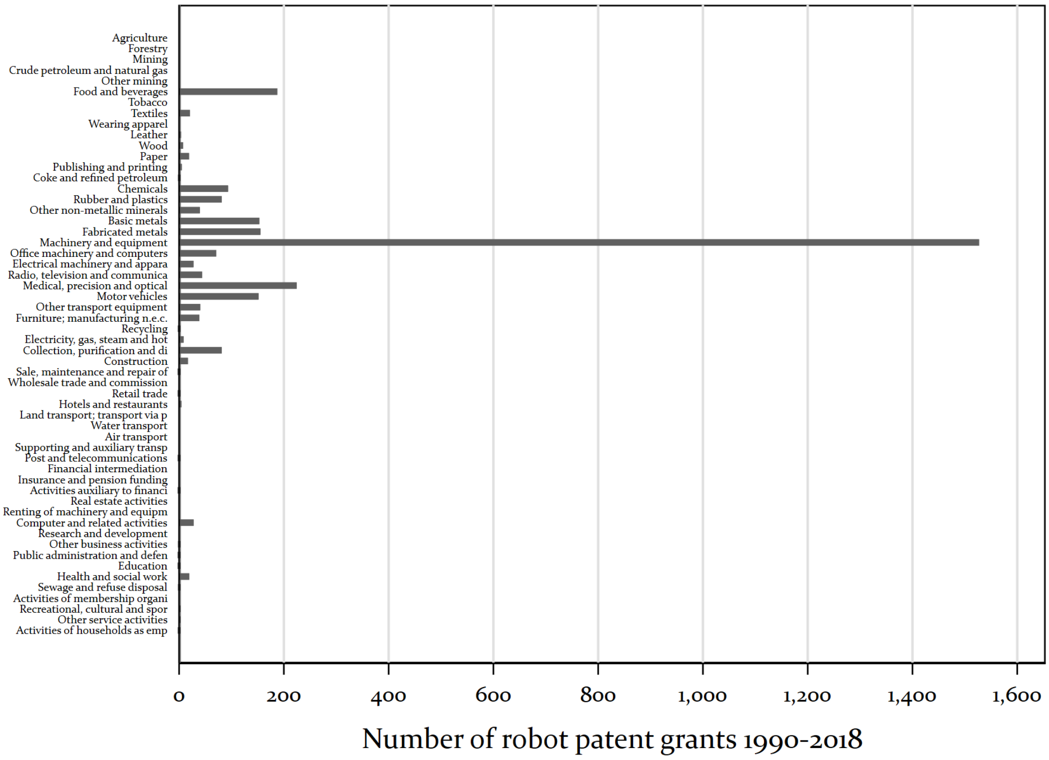
We then turn to administrative data on worker careers to analyze how workers adjust to AI. Our analysis indicates that AI exposure reduces both employment and earnings though the effects are still small on average. Moreover, AI leads to significant worker reallocation. More workers switch employers. While we see no impact on occupational mobility, many more workers switch industries. Workers in AI-exposed industries tend to move to similar industries that are less exposed to the new technology. We find that less-skilled and surprisingly older workers exhibit higher job mobility. However, the higher job mobility is beneficial as some workers, especially older workers, move to better-paying firms, indicating a better match.

The impacts of AI on the labor market require proactive policy responses. As workers' mobility and job-to-job transitions increase, policymakers should facilitate these transitions. Since the effects are strongest for low—and medium-skilled workers, developing and implementing training programs to equip them with the necessary skills to handle new tasks is crucial. For older workers, it is important to encourage lifelong learning and to create incentives for employers to hire and retain them.

In conclusion, AI profoundly impacts the labor market and reshapes work by changing the task content of occupations and increasing worker mobility across industries. While the immediate employment effects are still relatively small, the longer-term implications for job stability, skill requirements, and worker mobility are significant. As AI continues to evolve and integrate into more industries and occupations, ongoing research and policy measures will be important to ensure that the workforce can successfully navigate and benefit from these technological advancements.

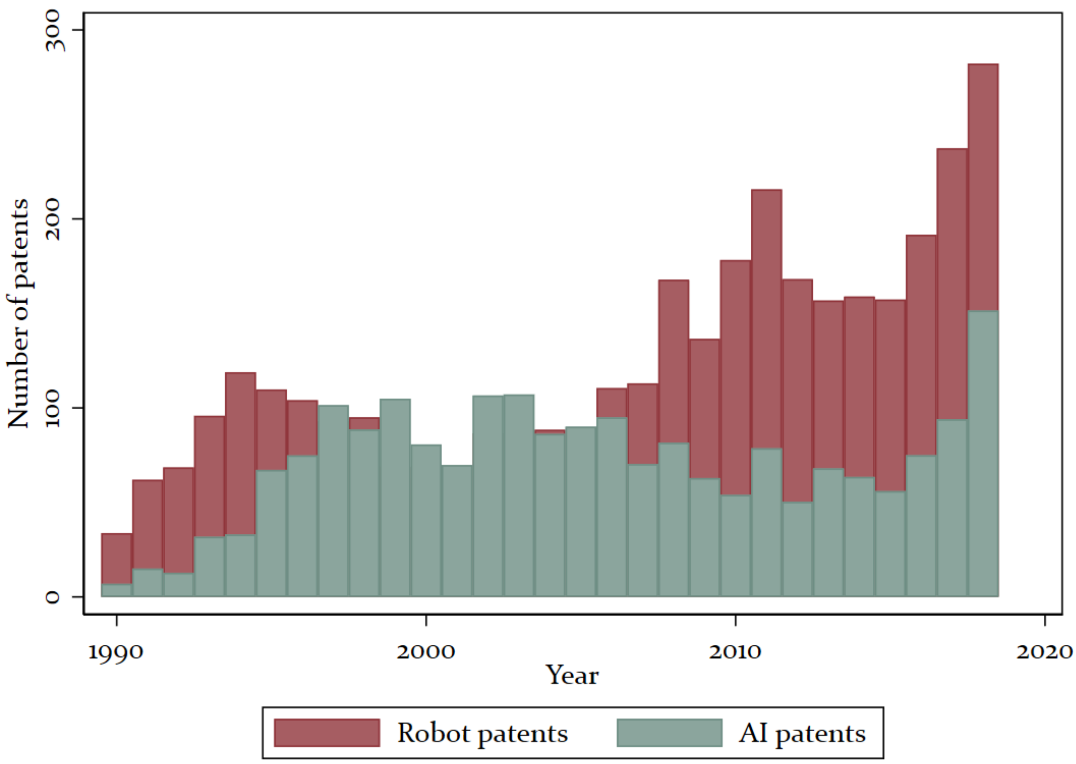
3.A Figures

Figure 3.A.1: Cumulative Robot Patents by Industry



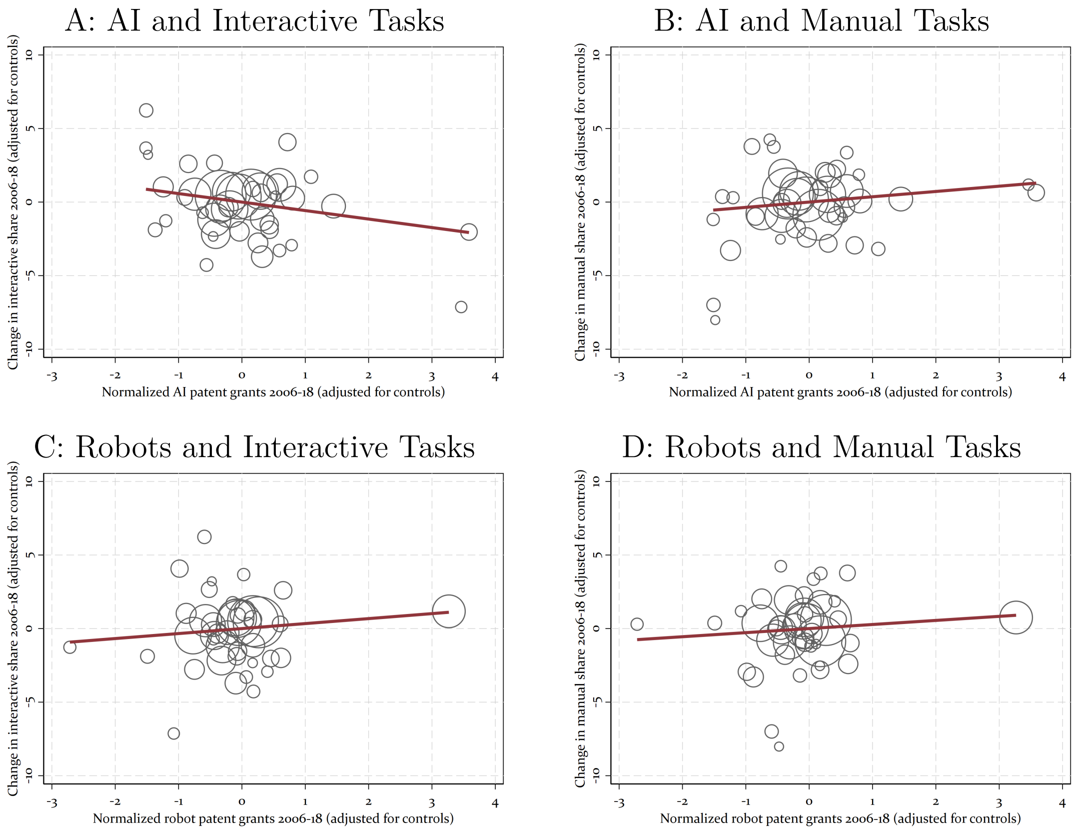
Note: This figure shows the cumulative number of robot patent grants between 1990 and 2018 across 2-digit industries. The top 3 industries in terms of the number of patent grants are: Manufacturing of machinery and equipment; manufacturing of medical, optical, and precision instruments; manufacturing of food and beverages.

Figure 3.A.2: Evolution of AI and Robot Patents over Time



Note: The figure shows the evolution in the number of robot patents and AI patents per year between 1990 and 2018.

Figure 3.A.3: AI, Robots, and Interactive and Manual Tasks



The figure shows the relationship between changes in task shares between 2006 and 2018 and AI and robot patents, respectively, between 2006 and 2018, adjusting for demographic and sector controls. Patent measures are normalized to have a mean of 0 and a standard deviation of 1. Demographic controls include the share of three education groups, five age groups, gender, and workers with German nationality. Sector controls include the manufacturing, service, and primary sector. The size of the circle denotes the number of employees in the industry in 2006. The figure focuses on industries with at least thirty observations in our sample in 2006.

3.B Tables

Table 3.B.1: Descriptives of Task Groups and Detailed Task Shares

	(1) All years	(2) 2006	(3) 2012	(4) 2018
	A: Task Groups			
	mean/sd	mean/sd	mean/sd	mean/sd
Routine tasks	23.67	23.89	24.04	23.09
	(15.09)	(15.70)	(14.88)	(14.63)
Analytical tasks	32.16	31.00	31.93	33.59
	(15.26)	(15.46)	(14.88)	(15.31)
Interactive tasks	25.06	25.29	25.14	24.75
	(13.07)	(13.41)	(13.03)	(12.74)
Manual tasks	19.11	19.83	18.90	18.56
	(14.36)	(14.87)	(14.09)	(14.07)
	B: Detailed Tasks			
	mean/sd	mean/sd	mean/sd	mean/sd
Monitoring/operating machines/technical processes	5.50	5.60	5.57	5.34
	(6.58)	(6.78)	(6.66)	(6.28)
Manufacturing/producing of goods/products	3.12	3.25	3.24	2.88
	(6.08)	(6.68)	(5.89)	(5.59)
Transporting, storing, shipping	6.36	6.51	6.40	6.16
	(7.74)	(7.77)	(7.73)	(7.71)
Measuring, quality checks	8.69	8.53	8.84	8.71
	(6.71)	(6.85)	(6.71)	(6.55)
Developing, researching, constructing	3.79	3.66	3.72	3.98
	(5.32)	(5.25)	(5.25)	(5.44)
Gathering information, investigating, documenting	9.78	9.52	9.76	10.08
	(6.66)	(6.69)	(6.68)	(6.59)
Promoting, marketing, advertising, PR	3.74	3.91	3.72	3.57
	(5.54)	(5.65)	(5.50)	(5.46)
Organizing/planning/preparing of work processes (of others)	8.08	7.57	7.93	8.75
	(6.39)	(6.36)	(6.25)	(6.50)
Teaching, training, educating	6.49	6.32	6.59	6.57
	(6.27)	(6.46)	(6.13)	(6.21)
Consulting, informing	10.54	10.72	10.48	10.40
	(6.71)	(6.85)	(6.77)	(6.51)
Buying, procuring, selling	4.30	4.33	4.36	4.22
	(5.71)	(5.84)	(5.72)	(5.55)
Working with computer/tablet	10.51	10.25	10.51	10.78
	(7.83)	(8.20)	(7.49)	(7.75)
Repairing	5.40	5.73	5.30	5.15
	(6.70)	(7.21)	(6.30)	(6.51)
Accomodating, hosting, preparing food	1.53	1.54	1.46	1.59
	(3.83)	(3.94)	(3.78)	(3.78)
Caring, healing	2.08	2.29	2.00	1.94
	(4.42)	(4.93)	(4.20)	(4.05)
Protecting, securing, guarding, regulating traffic	4.13	4.25	4.05	4.09
	(5.77)	(5.78)	(5.68)	(5.85)
Cleaning, waste disposal, recycling	5.97	6.02	6.10	5.79
	(7.64)	(7.76)	(7.67)	(7.50)

Note: Number of observations: 37,202. The table shows descriptives on task shares for all years in column (1) and separately for the years 2006, 2012, and 2018 in columns (2)-(4).

Table 3.B.2: Heterogeneity by Age

	Routine task share		Analytical task share	
	(1)	(2)	(3)	(4)
AI Exposure	-0.49	0.12	0.05	-0.39
	(0.36)	(0.38)	(0.31)	(0.34)
AI x Ages 26-35	0.47	0.22	-0.40	-0.18
	(0.34)	(0.34)	(0.33)	(0.34)
AI x Ages 36-65	1.01***	0.65	-0.30	-0.07
	(0.39)	(0.41)	(0.34)	(0.34)
R^2	0.39	0.36	0.40	0.38
	Interactive task share		**Manual task share**	
AI Exposure	0.75***	0.70***	-0.32	-0.44
	(0.22)	(0.25)	(0.28)	(0.29)
AI x Ages 26-35	-0.71**	-0.68**	0.64**	0.64*
	(0.27)	(0.29)	(0.31)	(0.33)
AI x Ages 36-65	-0.99***	-0.92***	0.28	0.33
	(0.23)	(0.26)	(0.30)	(0.32)
R^2	0.34	0.32	0.40	0.36
Demographic controls	X	X	X	X
State dummies	X	X	X	X
Year dummies	X	X	X	X
Sector dummies	X	X	X	X
2-digit occupation dummies		X		X
3-digit occupation dummies	X		X	
1-digit industry dummies		X		X

Note: Number of observations: 37,202. The dependent variables are task shares of individual i working in occupation o and industry j in year t measured in percent (0-100). The key independent variables are the cumulative number of AI patents from 1990 to 2018 standardized to have mean zero and standard deviation of one; and an interaction effect with an indicator for the age group of the worker. Sector controls include dummies for manufacturing, service, and primary sector. Time controls include dummies for survey years (t) 2006, 2012, 2018. Demographic controls include 3 education groups (university degree, vocational degree, less than vocation degree), gender, 5 age groups (18-25, 26-35, 36-45, 46-55, 56-65), a dummy for German nationality, and 16 federal state dummies. Regressions employ sample weights. Standard errors clustered at 2-digit industry-year level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 3.B.3: Robustness tests

Panel A: Routine Tasks	w/o German patents		No, patents		Log (1+patents)	
	(1)	(2)	(3)	(4)	(5)	(6)
AI Exposure	0.34***	0.64***	0.76***	1.40***	0.02***	0.03***
	(0.09)	(0.11)	(0.21)	(0.23)	(0.01)	(0.01)
Robot Exposure	-0.40***	-0.46***	-0.19***	-0.23***	-0.01***	-0.02***
	(0.05)	(0.07)	(0.02)	(0.03)	(0.00)	(0.00)
R^2	0.39	0.36	0.39	0.36	0.39	0.36
	5-year lag		3 categories		Intensive margin	
	(7)	(8)	(9)	(10)	(11)	(12)
AI Exposure	0.35***	0.64***	0.33***	0.70***	0.35***	0.65***
	(0.09)	(0.10)	(0.11)	(0.13)	(0.09)	(0.11)
Robot Exposure	-0.42***	-0.50***	-0.44***	-0.53***	-0.41***	-0.49***
	(0.06)	(0.07)	(0.07)	(0.08)	(0.05)	(0.07)
R^2	0.39	0.36	0.46	0.44	0.39	0.36
Panel B: Analytical tasks	w/o German patents		No, patents		Log (1+patents)	
	(1)	(2)	(3)	(4)	(5)	(6)
AI Exposure	-0.26***	-0.47***	-0.55**	-1.03***	-0.01	-0.02**
	(0.10)	(0.14)	(0.22)	(0.31)	(0.01)	(0.01)
Robot Exposure	0.09	0.20**	0.05	0.10***	0.00	0.01**
	(0.06)	(0.08)	(0.03)	(0.04)	(0.00)	(0.00)
R^2	0.40	0.38	0.40	0.38	0.40	0.38
	5-year-lag		3 categories		Only intensive margin	
	(7)	(8)	(9)	(10)	(11)	(12)
AI Exposure	-0.25**	-0.46***	-0.22*	-0.50***	-0.25**	-0.47***
	(0.10)	(0.14)	(0.12)	(0.18)	(0.10)	(0.14)
Robot Exposure	0.10	0.22***	0.17**	0.31***	0.10	0.23***
	(0.06)	(0.08)	(0.07)	(0.10)	(0.06)	(0.08)
R^2	0.40	0.38	0.48	0.45	0.40	0.38
Demographic controls	X	X	X	X	X	X
State dummies	X	X	X	X	X	X
Year dummies	X	X	X	X	X	X
Sector dummies	X	X	X	X	X	
2-digit occupation dummies		X		X		X
3-digit occupation dummies	X		X		X	
1-digit industry dummies		X		X		X

Note: Number of observations: 37,202. Columns (1) and (2) drop patents by German inventors. Columns (3) and (4) use the absolute number of patents (measured in 100), columns (5) and (6) the sum of log(1+patents) as the main explanatory variables. Columns (7) and (8) use a 5-year-lag, columns (9) and (10) code the task measure as zero (never), one (occasional), or two (frequent), and columns (11) and (12) study the intensive margin conditional on performing a task. * p<0.10, ** p<0.05, *** p<0.01.

Chapter 4

Digital Technologies, Job Quality and Employer-provided Training [1]

Digitalisation and the adoption of artificial intelligence (AI) technologies are fundamentally transforming the workplace, marking what many describe as the Fourth Industrial Revolution. This revolution leverages the power of the internet, smart sensors, and advanced microchips, enabling unprecedented interactions between machines and humans (Brynjolfsson and McAfee, 2014). Despite the growing importance of these technologies, their impact on labor markets, particularly on job quality, remains under-explored.

In this paper, I investigate the relationship between digital technologies and job quality for incumbent workers in Germany. Specifically, I examine how exposure to basic digital technologies (e.g., computers and computer-controlled machines) and advanced technologies (e.g., artificial intelligence and machine learning) affect working conditions and participation in employer-provided training. Additionally, I explore the roles of information and communication technology (ICT) investments and personnel management in shaping these outcomes. The OECD recently identified job quality as a key issue (2023), emphasizing the need for a comprehensive understanding of working conditions, job satisfaction, and work-life balance. Working

[1] I thank Christina Gathmann for her advice during this project. I am grateful to Julio Garbers, Terry Gregory, Alex Yarkin, Joël Machado, Felix Stips, Etienne Bacher, and participants at workshops and conferences at LISER, the University of Luxembourg, the German Federal Institute for Employment Research (IAB), and Trier University for valuable comments and suggestions.

conditions encompass valuable components of job quality like job content and context (Nikolova and Cnossen, 2020). Job quality can be measured in multiple dimensions, and the focus on working conditions follows from the job demands-resources model (Karasek, 1979; Demerouti et al., 2001; de Jonge et al., 2000). In this model, workers suffer from strain in their jobs when job demands like time pressure outweigh job resources such as decision autonomy (Bakker and Demerouti, 2007). Additionally, I investigate components of well-being such as job satisfaction and work-life balance that are closely related to job quality (Eurofound, 2022; Clark, 2015).

To estimate the effects of digitalisation on job quality, I use the Linked Personnel Panel (LPP-ADIAB)[2], a linked employer-employee survey from Germany, combined with administrative data covering the years 2012-2018. This dataset includes detailed information on job quality from employee surveys, firm characteristics and personnel management practices from employer surveys, and employment records, including spells, education, wages, and occupations. Each establishment is matched with data from the IAB Establishment Panel, providing insights into firm size, age, industry, location, and investment decisions.

I measure digitalisation using cross-sectional data on occupational exposure to basic and advanced digital technologies. These variables include measures of occupational susceptibility to computerization (Dengler and Matthes, 2018), routine task intensity (RTI) (Mihaylov and Tijdens, 2019) as well as exposure to AI (Felten et al., 2019) and machine learning (Brynjolfsson et al., 2018) [3].

I estimate models at the individual worker level, focusing on working conditions and participation in employer-provided training. Using regressions with a rich set of control variables, I exploit the panel dimension of the data by incorporating year and establishment fixed effects to control for general trends and unobserved time-invariant characteristics of the employers.

[2]For a detailed description of the LPP-ADIAB see Broszeit et al. (2017), Kampkötter et al. (2016) and Ruf et al. (2019).

[3]Measures like RTI and computer technology are frequently used in the literature as proxies for automation, primarily in routine tasks (see Autor et al. (2003) for an early example). In contrast, advanced technologies, such as artificial intelligence, are expected to affect occupations that are less reliant on routine tasks (Brynjolfsson et al., 2018; Agrawal et al., 2019, 2023).

My results show that exposure to advanced digital technologies is associated with improved working conditions and increased participation in employer-provided training. Conversely, high exposure to basic digital technologies correlates with worse working conditions and reduced training participation. These effects are particularly significant for male and older employees, highlighting the varying impacts across different demographic groups. Furthermore, ICT investments amplify the negative effects of basic technologies but enhance the positive effects of advanced technologies. Effective personnel management practices, such as regular employee interviews and feedback mechanisms, are found to mitigate some of the adverse impacts of digitalisation.

Digitalisation has important effects on job quality as introducing new digital technologies affects the tasks workers perform in their jobs and the organization of production (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019). Automating repetitive or dangerous tasks can improve job quality, for example, when machines take over physically demanding activities (Green, 2012; Gunadi and Ryu, 2021; Gihleb et al., 2022). Conversely, digitalisation can have negative effects on job quality by causing stress and automation anxiety, increasing surveillance, or diminishing the sense of purpose by automating tasks that employees enjoyed performing (Gerten et al., 2019; Schwabe and Castellacci, 2020; Nazareno and Schiff, 2021; Dengler and Gundert, 2021; Martin and Hauret, 2022). The negative effects of technostress are described extensively in the psychological literature (Tarafdar et al., 2007; Ragu-Nathan et al., 2008; Ayyagari et al., 2011; Gerdiken et al., 2021). Job quality is also closely related to subjective well-being, which is naturally important for employees. A large body of literature also documents a positive relationship between subjective well-being and performance (DiMaria et al., 2019; Bryson et al., 2017; Judge et al., 2001; Oswald et al., 2015). However, for firms to fully unlock the productivity potential of new digital technologies, it is important to restructure work processes (Agrawal et al., 2023), which can come with a strain on employees' well-being.

This study makes several contributions to the existing literature. First, while most studies on the labor market effects of digitalisation focus on the number of jobs (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014), or the automation risk of occupations (Frey and Osborne, 2017; Arntz et al., 2017), I investigate the relationship between digital technologies and job quality, exploring the mitigating role of employer-provided training for incumbent workers. I provide new empirical evidence for Germany, complementing studies like Giuntella et al. (2023) who find that AI does not negatively impact workers' mental health, or Arntz et al. (2024) who find that new digital technologies can have a negative impact on manual workers' physical health.

Unlike previous literature that centers on the displacement effects of automation and digitalisation (Acemoglu and Restrepo, 2019, 2020; Dauth et al., 2021; Bessen et al., 2019), I investigate effects on incumbent workers who remain employed but experience significant changes in working conditions.

Second, I explicitly compare the impact of basic technologies, such as computers and computer-controlled machines, with advanced technologies, such as artificial intelligence and machine learning. In a task-based approach (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019), different technologies affect different tasks in production, which leads to distinct effects on occupations and workers. In addition to the direct displacement effect, digital technologies also augment human labor in other tasks, reorganize the set of tasks humans perform on their jobs and change the organization of the production process (see Acemoglu and Restrepo, 2018; Acemoglu and Restrepo, 2019; Autor et al., 2003; Autor and Dorn, 2013; Bessen, 2016; Bloom et al., 2014; Lindbeck and Snower, 2000). In this context, basic digital technologies mostly automate routine tasks (Autor et al., 2003), increasing demand for complementary interactive tasks. More advanced technologies such as AI can perform more complex tasks in which humans previously had a comparative advantage (Brynjolfsson et al., 2018; Agrawal et al., 2019, 2023).

Finally, this paper underscores the dynamic relationship between technology and labor. It highlights the importance of employer strategies, such as training and personnel management practices, in adapting to technological changes. Bartel et al. (2007), for example, show that IT adoption leads to increasing skill requirements as the production process is reorganized. One way of dealing with changes in work processes and the introduction of new technologies is for employers to provide their employees with further training (Haepp, 2021; Lukowski et al., 2020; Wotschack, 2020). However, Brunello et al. (2023) show that employers could also reduce training provision after introducing advanced digital technologies if those substitute for trained workers. I contribute to this literature by incorporating the employer side in the analysis and providing evidence on how firms and employees adjust to digital technologies. I show that effective personnel management and targeted training can mitigate some of the adverse effects of digitalisation, enhancing workers' resilience to workplace changes.

The remainder of the paper is organized as follows: Section 4.1 introduces and describes the data used. Section 4.2 presents the empirical strategy, while the corresponding main results are shown in section 4.3. Additional results are provided in section 4.4 and a series of robustness checks in section 4.5. Section 4.6 concludes the paper.

4.1 Data

Studying the impact of digitalisation on job quality at an individual worker level imposes some challenging data requirements. While data on employees alone might be somewhat informative, many subjective measures can potentially be affected by firm differences, making adding data on the employer side necessary. In this study, I combine three different data sources, which are explained in more detail below. First, I use a linked employer-employee survey to measure working conditions, training participation, and personnel management. Second, administrative records provide demographic information and detailed occupational codes and wages for employees. Third, a set of variables measuring occupational exposure to basic and advanced digital technologies complements the survey and administrative data.

4.1.1 Linked Personnel Panel

To analyze job quality and employee training participation, I use the Linked-Personnel Panel (LPP), which is merged with administrative employment and establishment records of the Federal Institute for Employment Research (IAB). The data cover the years 2012-2018[4].

The LPP is a survey based on the IAB Establishment Panel, which is a large panel of approximately 16,000 establishments in Germany. From this panel, a sample of establishments and employees is drawn for the LPP survey. The sample is stratified by broad occupations, five sectors, and four regions, resulting in an average of 875 establishments and 7,000 employees across the five survey waves. Overall, the data is representative of German firms in manufacturing and services with more than 50 employees. Establishments are sampled repeatedly, and 43% are included in all waves of the survey, while 85% are included in at least two waves. In contrast, due to attrition, only 15% of employees appear in all survey waves. Therefore, they are treated as repeated cross-sections.

The survey provides the primary outcomes of interest related to working conditions and employer-provided training. I build an index for working conditions that comprises five items, each rated on a scale from 1 to 5. The items included are decision autonomy, task variety, time pressure, physical effort, and ambient conditions. They are coded such that a higher value implies better working conditions. The list of items is derived from the literature on job quality and the job demand-resources model (Bakker and Demerouti, 2007). For example, working under time pressure to meet tight deadlines is considered a job demand that can potentially lead to negative health outcomes for workers. At the same time, some of this can be offset if employees have more autonomy in making decisions and are more flexible in structuring their workload. Therefore, the item on decision autonomy can be classified as a job resource. In combination with the other items

[4]For a detailed description of the LPP-ADIAB see Broszeit et al. (2017), Kampkötter et al. (2016) and Ruf et al. (2019).

on working conditions such as physical effort or ambient conditions, the index captures an important dimension of job quality [5].

In addition, the survey includes a rich set of variables on employee characteristics that I use as control variables or additional outcomes. One example is wages, which can be considered as part of the quality of a job as well. However, in this setting, I do not include a worker's wage in my measure of job quality; rather, I include it in the empirical analysis as a control variable. This is because controlling for wages makes employees more comparable, as high (low) paying occupations might share common characteristics that are not directly observed in the survey.

One of the main advantages of the LPP is that it covers both the employee and the employer side. The employer survey focuses on personnel management practices. It provides additional information on firm characteristics like size, industry, ownership structure, and collective bargaining agreements, as well as on job characteristics like performance pay or the possibility of working from home.

The LPP survey is then linked to administrative employment records for each employee, providing detailed information on occupation, wage, age, gender, education, qualification, location, and more. Employer-side information can be supplemented by the Establishment History Panel and the IAB Establishment Panel, which surveys a broad range of topics. Questions about investments in information and communication technologies included in the Establishment Panel are especially relevant to this study. I use these questions to construct a variable measuring whether a firm invested in ICT equipment the year before the survey. This allows me to qualify the technology exposure at the employee level, assuming that firms with ICT investments are adopting more digital technologies.

4.1.2 Measures for Digital Technology Exposure

The digitalisation variables serve as measures for occupational exposure to digital technologies and can be defined in two broad categories. The first category is basic digital technologies, which refers to information and communication technologies

[5] As shown in Eurofound (2022), there exist additional dimensions of job quality, such as intrinsic job features or job prospects, that are not the focus of this study.

like computers, computer-controlled machines, and their applications. The second category is advanced digital technologies, which refer to technologies based on artificial intelligence that have the potential to affect a wider range of tasks compared to basic ICT, including decision-making (Agrawal et al., 2019).

I use two different measures to measure occupational exposure to basic digital technologies. The first one is a measure for computerization and was developed by Dengler and Matthes (2018). They estimate an automation potential due to computerization for occupations in Germany based on the database BERUFENET [6]. This database includes a comprehensive register of tasks and work activities, which are subsequently classified based on their susceptibility to computerization. These tasks are then aggregated at the occupation level. Occupations with a high share of computer-susceptible tasks are assumed to be at higher risk of automation. Another approach is to indirectly measure the exposure to computerization and ICT based on the routine task intensity (RTI) of an occupation, following Autor et al. (2003). This indirect approach exploits the fact that routine tasks were the ones most affected by the rise in ICT technologies and computerization, leading to the decline in employment in routine-intensive occupations (Autor and Dorn, 2013; Goos et al., 2014). I use a routine task intensity index for European occupations developed by Mihaylov and Tijdens (2019). Tables 4.A.1 and 4.A.2 in the appendix show the 10 occupations with the highest and lowest scores for routine task intensity and computer substitution potential, respectively. It becomes visible that the occupations with the highest RTI are found in office and administrative work and a range of manufacturing occupations, representing routine cognitive as well as routine manual tasks. The top occupations in computer substitution potential share this fact but are even more focused on manufacturing, with metal-making and precision mechanics having the highest scores. Occupations with low RTI and computer substitution scores include engineering, pharmacy, teaching, and care. These occupations require a combination of non-routine cognitive, non-routine manual, and interactive tasks.

[6]The BERUFENET database is a database for occupational tasks and abilities in Germany, similar to the O*NET database in the U.S.

To measure occupational exposure to advanced digital technologies, I use two measures developed by Felten et al. (2018) and Brynjolfsson et al. (2018). They capture the exposure of occupations to artificial intelligence and machine learning. The measures share a common approach with the computerization measure of Dengler and Matthes (2018), starting at the task level to identify which tasks can potentially be performed by AI and machine learning. Occupational exposure is then calculated based on the proportion of each task within an occupation [7]. Compared to basic digital technologies, the tasks affected are different and often require higher skill levels. One example is the automation of prediction tasks, which is one of the strongest areas of artificial intelligence, as argued by Agrawal et al. (2019). Tables 4.A.3 and 4.A.4 in the appendix show the top and bottom 10 occupations for AI exposure and machine learning suitability. Occupations with both high AI exposure and ML suitability can be found in white-collar work such as accounting, HR management, or secretaries, as well as in sales and public administration. The exposure is lowest in occupations with a high share of non-routine manual tasks such as cleaning services, metalworking, or building construction.

Table 4.1 presents summary statistics for the main outcome and control variables as well as for the digitalisation measures, which are normalized to a range between 0 and 1 to make them better comparable.

[7] The measures from Felten et al. and Brynjolfsson et al. are based on US occupational data (O*NET) and are mapped to German occupations using a crosswalk from isco08 to the kldb2010 classification. Similar crosswalks have been used in Goos et al. (2014) and Sorgner (2017).

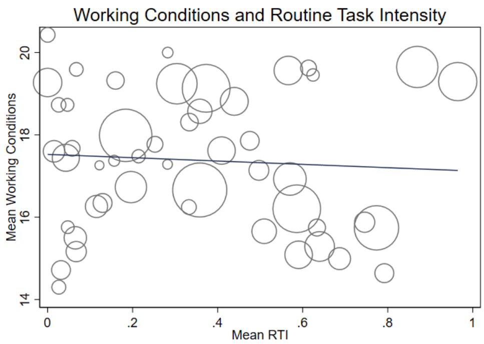
Table 4.1: Summary statistics

	Observations	Mean	Std. Dev.	Min	Max
Outcome variables:					
Working conditions	21,122	17.47	3.27	5	25
Training participation	21,152	0.39	.48	0	1
Job satisfaction	21,157	7.46	1.75	0	10
Sick days	14,959	15.80	23.15	1	230
Well-being	21,038	14.40	5.12	5	30
Work-life balance	9,684	2.24	1.22	1	5
Digitalisation Measures:					
Routine Task Intensity	21,176	.4266	.3652	0	1
Computerization	21,176	.5542	.2498	0	1
AI Exposure	21,176	.5359	.2625	0	1
Machine Learning Suitability	21,176	.6883	.1410	0	1
Control variables:					
Age	21,176	47.19	10.24	18	67
Male	21,176	0.71	0.45	0	1
Education	21,128	3.38	1.15	1	8
Qualification	21,155	2.42	1.63	1	8
Wage (imputed)	21,124	137.12	85.02	0.42	988.46
Firm size	21,138	3336.79	11630.61	1	65229
Leadership	21,151	0.28	0.45	0	1
Fulltime	21,147	0.86	0.34	0	1

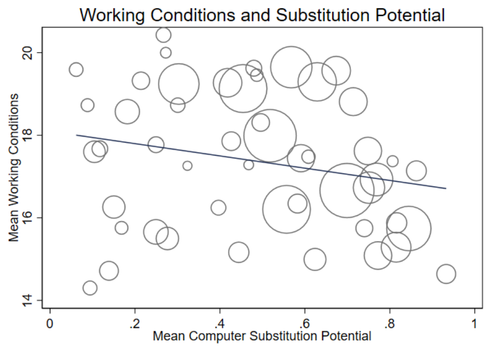
The following figures 4.1 and 4.2 depict the correlation between the main explanatory variables measuring technology exposure and the main outcome variables working conditions and training participation at the occupational level. In figure 4.1, occupations with a high share of routine tasks (panel a) and a high risk of computer substitution (panel b) show a slight negative correlation with the working conditions index, which seems not to be driven by the size of the occupations observed. On the other hand, even without controlling for individual factors, exposure to AI and machine learning shows a positive correlation with the working conditions index at the occupational level, as can be seen in panels c) and d) of figure 4.1.

Figure 4.2 presents correlations for participation in employer-provided training and technology exposure. While the observed correlations are less strong than for the working conditions index, occupations with a high routine task intensity or a high computer substitution potential have a lower average training participation as

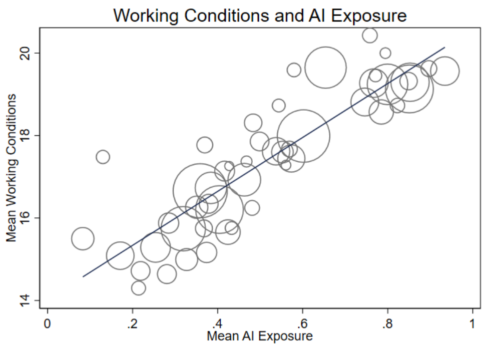
Figure 4.1: Correlation between digitalisation measures and working conditions



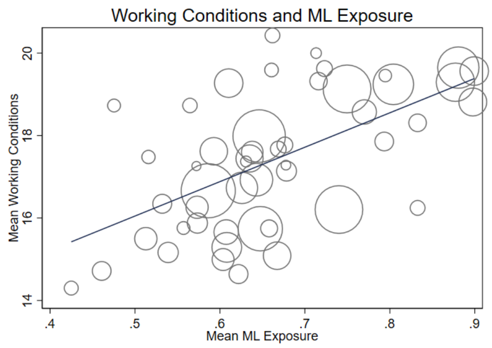
(a) Routine Task Intensity and Working Conditions



(b) Computers and Working Conditions



(c) AI Exposure and Working Conditions

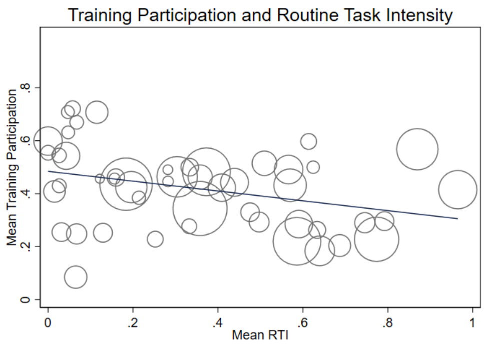


(d) ML Exposure and Working Conditions

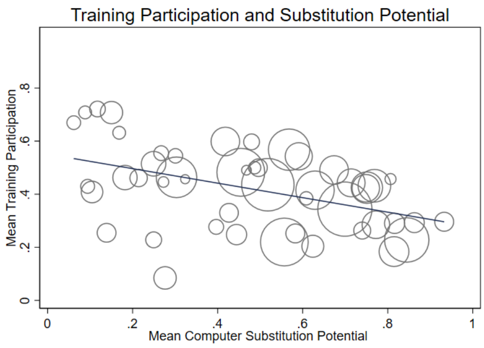
Note: All four graphs in the panel show correlations at the 3-digit occupation level (according to the kldb2010 classification). Individual observations have been aggregated to 29 occupations. Occupations with less than 20 workers have been grouped with similar occupations to comply with data protection rules. Working conditions are measured as averages over time and occupations, exposure measures are at the occupation level. The size of the markers represents the number of employees in the occupation.

shown in panels a) and b) of figure 4.2. Turning to advanced technologies, there is a positive correlation between AI exposure and training participation (see panel c) of figure 4.2) while the correlation between ML exposure and training participation is close to zero (see panel d) of figure 4.2).

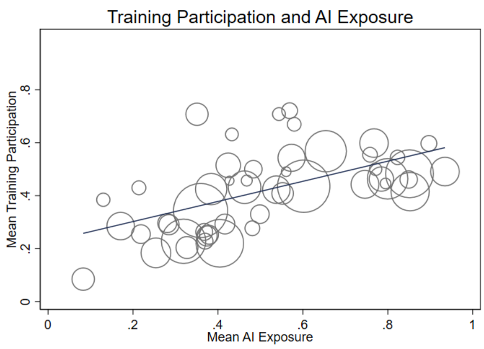
Figure 4.2: Correlation between digitalisation measures and training participation



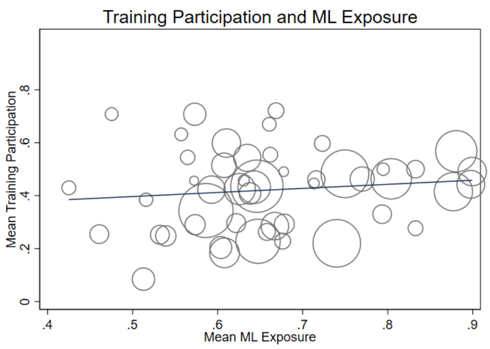
(a) Routine Task Intensity and Training Participation



(b) Computers and Training Participation



(c) AI Exposure and Training Participation



(d) ML Exposure and Training Participation

Note: All four graphs in the panel show correlations at the 3-digit occupation level (according to the kldb2010 classification). Individual observations have been aggregated to 29 occupations. Occupations with less than 20 workers have been grouped with similar occupations to comply with data protection rules. Training participation is measured as average over time and occupations, exposure measures are at occupation level. The size of the markers represents the number of employees in the occupation.

4.2 Empirical Strategy

The empirical strategy builds on employees' occupational exposure to digital technologies and the variation in working conditions over time. While the actual usage of digital technologies is not directly observed at the worker level, I assume that high occupational exposure increases the likelihood of technology adoption. Establishments also vary in whether they adopt a given technology. I use data on investment decisions from the IAB Establishment Panel as a proxy for technology adoption at the establishment level. Investments in ICTs can be regarded as investments in basic digital technologies and as laying the foundation for adopting advanced technologies. Consequently, worker-level exposure is likely to differ between high and low-adoption firms, even for workers in the same occupation.

The focus of this study is incumbent workers who continue to work at their employer but can experience changes in working conditions due to a shift in tasks caused by technological advances. I also observe workers who still perform the same tasks on their jobs but with changing intensities. Hence, this study does not aim to estimate the displacement effects of new technologies but rather to study the effects of digitalisation on currently employed workers. For workers remaining in their jobs, digital technologies can negatively affect working conditions by inducing stress and cognitive overload, leading to reduced subjective well-being and job satisfaction. However, if technology automates dangerous or disliked tasks, the change in job content could result in positive outcomes and increased worker well-being. The net effect is an open question ex-ante.

In this setting, variation comes from employees working in different occupations, which vary in their technology exposure. The advancement of digital technologies opens up new possibilities for structuring work processes, and the tasks that workers perform are likely to change. While some occupations are naturally more prone to digitalisation than others, technology adoption also depends on employers. For example, employers decide whether to provide their employees with new hardware or software and whether to assist them in adapting to the new technologies. Besides this, employers can vary by a range of time-variant or invariant characteristics. I address the former by including control variables such as firm size and the latter by including establishment fixed effects. By controlling for all unobserved, time-invariant differences across firms using fixed effects, I essentially compare employees in different occupations within the same firm to each other over time. The advantage of this approach is that it allows for filtering out more of the firm-specific factors that contribute to working conditions or training participation and, therefore, for clearer identification of the effect of digitalisation on these outcomes.

All outcome variables are measured at the individual worker level. Most of these variables are items from the LPP employee survey, coded from 1 to 5. For the working conditions, I aggregate them to an index ranging from 5 to 25. The training variable is a binary response variable, equal to one if the employee participated in training that year and zero otherwise. The LPP employee section includes self-reported survey questions on additional outcomes such as job satisfaction, well-being, and health status. A more objective health measure is the number of individual sick days per year, which I directly obtain from the social security records.

Using this set of outcomes and the digitalisation measures, I estimate regression equations of the following form:

$$y_{i,o,t,f} = \beta_0 + \beta_1 digi_{i,o} + \beta_2 X_{i,o,t,f} + \delta \text{establishment}_f + \gamma \text{year}_t + u_{i,o,t,f} \qquad (4.1)$$

where $y_{i,o,t,f}$ is either working conditions, training participation, or one of the additional outcomes of worker i in occupation o, year t, and firm f. $digi_{i,o}$ is one of the four occupation-level digitalisation measures used separately in the regressions. The coefficient of interest is β_1, which captures the impact of a higher occupational digitalisation exposure on the outcome variable $y_{i,o,t,f}$. $X_{i,o,t,f}$ includes a rich set of control variables such as age, gender, highest qualification, wage, and whether they work in a leadership position or full-time. These controls are included to address potential problems of omitted variable bias, which can arise if there are relevant variables that influence both technology exposure and job quality but are not included in the model. For example, if more educated employees are better at adopting new technologies and at the same time more satisfied with their working conditions, excluding measures of employee education or skill levels could introduce omitted variable bias.

Other potential threats to identification could arise if working conditions and technology adoption are endogenous to firms. For example, if larger firms invest more resources in technology adoption and, at the same time, in programs to improve job quality for their employees. Then, the estimated effect of digitalisation on working conditions may be biased. To address this concern, I control for additional employer characteristics that vary over time. I incorporate establishment size and other firm characteristics as control variables in $X_{i,o,t,f}$.

Exploiting the panel dimension of the establishment data, I control for a general time trend in the outcomes by including year fixed effects. Further, I include establishment fixed effects to control for unobserved firm-specific and time-invariant characteristics that influence both the implementation of new technologies and working conditions or training, which can potentially introduce bias. By using establishment fixed effects, the identifying variation comes from employees in different occupations at the same establishment. Therefore, the model essentially uses the changes in outcomes for individuals in different occupations within the same firm to identify the effect of digitalisation exposure while controlling for any fixed characteristics of the firm itself. Using establishment fixed effects requires companies to be in the sample for at least two survey waves. Since attrition is less problematic for establishments than employees, this requirement is met for around 85% of establishments. I estimate linear probability models with the same set of control variables and fixed effects for binary outcomes like training participation.

Another potential threat to identification is selection bias if firms that are investing in ICT technologies are also the ones with the best working conditions. To investigate this selection bias, I classify firms into investing and non-investing categories based on information from the Establishment Panel. A firm is considered investing if it has invested in ICT technologies in the year preceding the LPP survey and non-investing otherwise. I then estimate similar regressions as in equation (1) separately for investing and non-investing firms. However, it is important to acknowledge that splitting the sample into investing and non-investing firms does not fully address the selection bias. Firms that choose to invest in ICT may differ systematically from those that do not in ways that also affect working conditions and training participation. These differences could include factors that are not fully captured by the available control variables. By splitting the sample, I aim to provide preliminary insights into how the effects of digitalisation differ between investing and non-investing firms. While this approach cannot completely rule out selection bias, it helps to highlight potential differences in the impact of digitalisation across different types of firms.

4.3 Results: Working Conditions and Training

This section presents the main results obtained from regressions based on equation (1). I investigate the effect of technology exposure on job quality, as measured by the working conditions index, and on participation in employer-provided training.

The results for the working conditions are reported in Table 4.2. All estimations in columns (1) through (4) consistently incorporate the same control variables and fixed effects as detailed in the table notes. The main finding is the contrast between the negative effect of basic digital technologies and the positive effect of advanced technologies.

As shown in columns (1) and (2), a higher routine task intensity and a higher computerization score are negatively related to the working conditions index. The estimated coefficients translate into a decline in the working conditions index of up to 2.5 points on the scale ranging from 5 to 25 and are statistically significant at the 5% (column 1) and 1% (column 2) levels. An increase of the computer substitution potential by one standard deviation leads to a decrease in the working conditions index of 0.63 points. In contrast, exposure to advanced digital technologies, such as AI and machine learning, is positively related to the working conditions scale, exhibiting an increase of up to 4.5 points or 1.2 standard deviations, based on the AI exposure measure.

Accounting for the observed control variables and the inclusion of establishment fixed effects, it becomes clear that workers in occupations with higher exposure to basic digital technologies encounter poorer working conditions, while those in occupations with greater exposure to advanced digital technologies experience more favorable working conditions. Other factors correlated with working conditions include age, qualification, wage, and holding a leadership role, all of which are positively associated with working conditions.

Table 4.2: Digitalisation and Working Conditions

Working conditions index	(1)	(2)	(3)	(4)
Basic digital technologies:				
Routine Task Intensity	-0.508**			
	(0.226)			
Computerization		-2.552***		
		(0.257)		
Advanced digital technologies:				
AI Exposure			4.565***	
			(0.325)	
Machine Learning Suitability				4.318***
				(0.414)
Control variables:				
Age	0.010*	0.007*	0.008*	0.009
	(0.005)	(0.004)	(0.004)	(0.006)
Male	-0.598***	-0.422**	0.136	-0.173
	(0.206)	(0.174)	(0.124)	(0.169)
Education	0.205**	0.135	-0.004	0.138
	(0.091)	(0.089)	(0.083)	(0.095)
Qualification	0.175***	0.133***	0.096***	0.183***
	(0.044)	(0.037)	(0.034)	(0.040)
Wage	0.007***	0.005***	0.003***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm size	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Leadership	0.541***	0.470***	0.500***	0.594***
	(0.085)	(0.078)	(0.079)	(0.079)
Fulltime	-0.466***	-0.439***	-0.234*	-0.373***
	(0.147)	(0.144)	(0.138)	(0.133)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.288	0.304	0.349	0.306
Observations	20974	20974	20974	20974

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Control variables include age, gender, education, qualification, wage, establishment size, leadership, and full-time employment. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Next, I investigate the relationship between technology exposure and training participation. Table 4.3 presents the outcomes of linear probability models, estimating the association between exposure to digital technologies and the probability of participating in employer-provided training. Analogous to the working conditions case, the RTI and computerization effects contrast with those of AI and machine learning, as indicated by the negative coefficients in columns (1) and (2) and the positive coefficients in columns (3) and (4).

Employees in occupations with the highest routine task intensity are approximately 7.2% less likely to participate in training offered by their employer as compared to those with the lowest RTI. A higher computerization risk corresponds to an even more pronounced decrease in the likelihood of training participation of 22.4%. In turn, higher AI or machine learning exposure increases the likelihood of participating in employer-provided training by about 23.9% and 10% on average, respectively.

With respect to other factors influencing training participation, it is apparent that older employees are less likely to participate in training, while higher qualifications and wages are positively correlated with training participation. Also, holding a leadership role is associated with increased training participation.

These results can be interpreted within a skill-based framework, where high-skilled employees possess a comparative advantage in performing complex tasks that require additional training. Consequently, these employees exhibit a higher propensity to receive training. Occupations characterized by a high share of routine tasks and high computerization scores tend to employ mainly low- and medium-skilled workers, who are less likely to receive employer-provided training. In contrast, workers in AI-intensive occupations tend to be more highly skilled and, therefore, more likely to participate in training programs.

One possible explanation for these findings is that advanced digital technologies, such as AI and machine learning, necessitate continuous learning and skill development, prompting employers to invest more in training for employees exposed to these technologies. On the other hand, basic digital technologies that automate routine tasks may reduce the perceived need for training, as the tasks being automated typically require lower skill levels. The contrast between training provision for AI-exposed employees and those exposed to more basic digital technologies highlights an important consideration in the debate on training initiatives. While the argument for training high-skilled employees aligns with the notion of leveraging comparative advantages, there is also an argument for upskilling less-skilled employees to address skill shortages. However, the results suggest that in the context of employer-provided training studied here, training initiatives are not specifically aimed at upskilling lower-skilled workers.

As outlined in the empirical strategy section, the extent to which an employee is exposed to digital technologies depends not only on their occupation but also on their employer. While individual technology adoption can not be observed in my data, I use information from the Establishment Panel on firms' ICT investment decisions, which serves as a proxy for establishment-level technology adoption. Under the hypothesis that firm-level technology adoption increases the likelihood that employees will work with new technologies, we would expect stronger effects for employees in investing firms in the regression analysis. In this framework, ICT investment can be seen as a direct investment in basic digital technologies as well as an input into adopting more advanced technologies that require a good IT infrastructure as a basis.

Table 4.3: Digitalisation and Training Participation

Training participation	(1)	(2)	(3)	(4)
Basic digital technologies:				
Routine Task Intensity	-0.072*			
	(0.038)			
Computerization		-0.224***		
		(0.039)		
Advanced digital technologies:				
AI Exposure			0.239***	
			(0.041)	
Machine Learning Suitability				0.101
				(0.066)
Control variables:				
Age	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.034	-0.015	0.010	-0.016
	(0.028)	(0.028)	(0.028)	(0.026)
Education	0.032***	0.026***	0.021***	0.031***
	(0.008)	(0.007)	(0.008)	(0.008)
Qualification	0.017**	0.014**	0.014**	0.018**
	(0.007)	(0.007)	(0.006)	(0.007)
Wage	0.001***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Leadership	0.102***	0.097***	0.102***	0.106***
	(0.020)	(0.019)	(0.019)	(0.019)
Fulltime	-0.018	-0.016	-0.007	-0.017
	(0.027)	(0.028)	(0.028)	(0.025)
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.221	0.226	0.227	0.220
Observations	21003	21003	21003	21003

Notes: All models estimated are linear probability models with establishment and year fixed effects included. Training participation is one if the employee participated in training in the respective year and zero otherwise. Control variables include age, gender, education, qualification, wage, establishment size, leadership, and full-time employment. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.4: Digitalisation and Working Conditions - ICT Investments

	No Investment	Invest	No Investment	Invest	No Investment	Invest	No Investment	Invest
Basic digital technologies:								
Routine Task Intensity	-0.365	-0.601*						
	(0.227)	(0.308)						
Computerization			-2.031***	-2.815***				
			(0.360)	(0.305)				
Advanced digital technologies:								
AI Exposure					5.120***	4.397***		
					(0.376)	(0.431)		
Machine Learning Suitability							5.082***	4.134***
							(0.643)	(0.453)
Control variables:								
Age	0.003	0.011	0.003	0.007	0.002	0.007	0.002	0.010
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
Male	-0.907***	-0.492*	-0.775***	-0.296	-0.198	0.213	-0.472**	-0.095
	(0.197)	(0.270)	(0.191)	(0.215)	(0.175)	(0.149)	(0.190)	(0.209)
Education	0.220***	0.181	0.187***	0.099	0.001	-0.013	0.158**	0.119
	(0.071)	(0.121)	(0.070)	(0.118)	(0.066)	(0.113)	(0.066)	(0.129)
Qualification	0.092*	0.201***	0.065	0.151***	0.044	0.112**	0.102*	0.209***
	(0.054)	(0.060)	(0.054)	(0.048)	(0.045)	(0.044)	(0.054)	(0.054)
Wage	0.007***	0.007***	0.005***	0.006***	0.001	0.003***	0.007***	0.007***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Firm size	0.000***	-0.000*	0.000***	-0.000**	0.000***	-0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leadership	0.843***	0.467***	0.823***	0.395***	0.788***	0.441***	0.801***	0.544***
	(0.145)	(0.124)	(0.145)	(0.102)	(0.139)	(0.113)	(0.133)	(0.108)
Fulltime	-0.079	-0.594***	-0.064	-0.564***	0.143	-0.337**	-0.067	-0.496***
	(0.260)	(0.183)	(0.257)	(0.168)	(0.227)	(0.166)	(0.262)	(0.165)
ICT Investment	No	Yes	No	Yes	No	Yes	No	Yes
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.392	0.278	0.400	0.297	0.456	0.335	0.414	0.294
Observation	4741	13384	4741	13384	4741	13384	4741	13384

Notes: All models estimated are OLS with establishment and year fixed effects included. ICT investment is measured as binary variable and is one if the company invested in the previous year. Control variables include age, gender, education, qualification, wage, establishment size, leadership, and full-time employment. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.4 reports estimates of regressing the working condition index on technology exposure at the worker level, conditional on the fact that a firm invests in ICT. I split the sample into two groups: Employees at firms that invest in ICT and those that do not. Columns (1), (3), (5), and (7) run regressions for employees who work at firms without ICT investments, whereas columns (2), (4), (6), and (8) report coefficients for employees that work at investing firms.

The negative effects of basic digital technologies on working conditions are more pronounced for investing firms, confirming the hypothesis that ICT investments foster the adoption of new technologies and, therefore, lead to more pronounced effects of digital technologies on employees.

For advanced technologies, the effects stay positive but appear smaller in investing than in non-investing firms. This shows that, at least for basic digital technologies, the organization of production plays an important role. In firms that do not invest in ICT, however, employees are less exposed to the negative consequences of digitalisation. At the same time, firms are likely to forego potential productivity gains associated with technology investments.

Table 4.5: Digitalisation and Training Participation - ICT Investments

	No Investment	Investment	No Investment	Investment	No Investment	Investment	No Investment	Investment
Basic digital technologies:								
Routine Task Intensity	-0.179***	-0.072**						
	(0.045)	(0.034)						
Computerization			-0.213***	-0.227***				
			(0.062)	(0.055)				
Advanced digital technologies:								
AI Exposure					0.202***	0.271***		
					(0.053)	(0.048)		
Machine Learning Suitability							-0.093	0.139**
							(0.119)	(0.057)
Control variables:								
Age	-0.003***	-0.006***	-0.003***	-0.006***	-0.003***	-0.006***	-0.003**	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Male	0.031	-0.033	0.057*	-0.014	0.073**	0.015	0.039	-0.013
	(0.029)	(0.031)	(0.034)	(0.027)	(0.032)	(0.026)	(0.028)	(0.028)
Education	0.030***	0.031***	0.028***	0.024***	0.023**	0.019**	0.033***	0.029***
	(0.011)	(0.009)	(0.010)	(0.009)	(0.011)	(0.009)	(0.011)	(0.010)
Qualification	-0.014	0.026***	-0.014	0.022***	-0.012	0.021***	-0.010	0.027***
	(0.011)	(0.009)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)	(0.009)
Wage	0.000**	0.001***	0.001**	0.001***	0.000**	0.000**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm size	0.000*	-0.000	0.000*	-0.000	0.000*	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leadership	0.123***	0.112***	0.119***	0.108***	0.118***	0.113***	0.121***	0.118***
	(0.022)	(0.022)	(0.022)	(0.020)	(0.022)	(0.022)	(0.022)	(0.022)
Fulltime	0.019	-0.022	0.012	-0.020	0.018	-0.007	0.007	-0.020
	(0.033)	(0.027)	(0.033)	(0.027)	(0.033)	(0.027)	(0.033)	(0.026)
ICT Investment	No	Yes	No	Yes	No	Yes	No	Yes
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.305	0.234	0.301	0.238	0.301	0.242	0.297	0.233
Observations	4754	13403	4754	13403	4754	13403	4754	13403

Notes: All models estimated are OLS with establishment and year fixed effects included. ICT investment is measured as binary variable and is one if the company invested in the previous year. Control variables include age, gender, education, qualification, wage, establishment size, leadership, and full-time employment. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Regarding training participation, as reported in table 4.5, the differences between investing and non-investing firms are less pronounced, and the initially observed pattern of results persists. The negative effect associated with a high routine task intensity is smaller for investing firms, whereas the effect associated with a higher computerization risk is basically unchanged. In contrast, exposure to advanced digital technologies positively affects training participation in investing firms, compared to non-investing firms. For firms that do not invest in ICT, the effects are smaller in the case of AI exposure or even negative but statistically not significant in the case of ML exposure.

4.3.1 Results by Age and Gender

This section investigates the relationship between digital technologies, working conditions, and training participation across different age groups and by gender. Age groups are defined as young (18-29), middle-aged (30-49), and older (50 and above). We would expect differential results, especially by age, as younger workers are generally perceived to be more flexible and open to learning new skills. There could also be differences by gender if, for example, women are more flexible in adopting new skills than men or tend to select into occupations with higher AI exposure and better working conditions.

As shown in panel A of table 4.A.6 in the appendix, exposure to advanced digital technologies is associated with better working conditions across all age groups. The most pronounced effect is observed among middle-aged workers. Conversely, the negative association between exposure to basic digital technologies and working conditions is primarily driven by older workers. For this group, the effect is both negative and statistically significant, with the estimated coefficients being larger than those for the entire sample.

One explanation for this finding is the hypothesis of technostress, where the introduction of new technology negatively affects employees' well-being. While older employees are more experienced in their jobs and have more task-specific human capital, they might be less flexible in adjusting to new technologies and environments than their younger colleagues. The introduction of new technologies and the accompanying reorganization of work processes could lead to more stress for older workers than for younger ones.

Exposure to basic digital technologies does not significantly affect working conditions for younger workers. However, higher routine task intensity or a higher computer automation risk negatively affects middle-aged and older workers. The coefficient on computerization is greatest for older workers, at -2.64, and significant at the 1% level.

Regarding training participation, panel B of table 4.A.6 in the appendix shows that younger workers are generally less affected by both basic and advanced technologies, with most coefficients not reaching statistical significance, except for increased participation associated with machine learning suitability. On the other hand, middle-aged and older workers exposed to basic digital technologies are less likely to participate in training. The effects of advanced digital technologies on training for these age groups are mixed and less significant.

Overall, advanced digital technologies enhance working conditions for all age groups, especially middle-aged workers. Basic digital technologies negatively affect older workers' job quality, while younger workers show little impact on training participation from both technology types.

Table 4.A.7 in the appendix shows the results by gender. Female and male workers could react differently to new technologies, leading to gender differences in the effects of digital technologies on job quality. Another explanation for potential differences could be occupational sorting, where male and female workers sort into different occupations with better working conditions and higher AI exposure, or vice versa.

Basic digital technologies negatively impact working conditions for men more than for women, with men showing stronger negative coefficients for routine task intensity and computerization. This indicates that women are less affected by the negative impacts of routine task intensity and computerization on working conditions compared to their male counterparts. Advanced digital technologies positively affect working conditions for both genders, with women benefiting slightly more.

Regarding training participation, basic digital technologies reduce training participation for both genders, particularly for men. For male workers, exposure to routine tasks and computerization significantly lowers training participation, reflecting reduced opportunities or willingness to engage in training when exposed to these technologies. Women show a positive relationship between advanced digital technologies and training participation, consistent with the overall sample, but experience a smaller decline in training participation from basic digital technologies compared to men.

These findings suggest that basic digital technologies adversely affect men in terms of working conditions and training participation. The stronger negative impact on men could be due to their higher likelihood of engaging in routine and automatable tasks. In contrast, women seem more resilient to the negative impacts on working conditions but still experience a decline in training participation due to basic digital technologies. The positive effects of advanced digital technologies on job quality and training participation are observed for both genders, with women particularly benefiting from increased training opportunities. This may reflect greater openness to learning new skills associated with AI and machine learning among female workers. One potential caveat to this analysis is that the sample includes considerably fewer female workers than male workers, which may influence the generalizability of the findings.

4.3.2 Training and Personnel Management as Mitigating Factors

This section investigates factors that potentially mitigate the negative effects of basic digital technologies on employees or further enhance the positive effects of advanced technologies. While the previous sections revealed that digitalisation affects the likelihood of participating in employer-provided training, this section studies whether training participation actually mitigates the negative impacts of basic digital technologies and amplifies the positive effects of advanced digital technologies.

Additionally, I explore the role of employers by analyzing whether specific personnel management practices mediate the impact of digitalisation on working conditions and training. The rationale behind this analysis is that employers are ultimately responsible for the introduction of new technologies and can provide employees with support to facilitate technology adoption.

4.3.2.1 Employer-provided Training

As shown in section 4.3, digitalisation affects the likelihood of participating in employer-provided training. The training itself can also serve as a mediating factor on the effect of digitalisation on working conditions. This occurs when training enhances adaptation to new technology and counteracts technostress.

In this section, I present evidence that conditional on participating in employer-provided training, the negative effects of basic digital technologies on employees are substantially weaker. Table 4.A.8 shows the results for regressions of working conditions on digitalisation measures for two groups of employees, those who did participate in training and those who did not.

The results indicate that for employees who participate in training, the negative effects of basic digital technologies on working conditions are less pronounced. For advanced technologies, the effects are similar but slightly weaker, suggesting that training does not further enhance the positive effects of advanced technologies.

Employer-provided training is a valid strategy to soften negative impacts on working conditions for exposure to basic digital technologies. However, when interpreting these results, it is important to take into account that selection into training is not random. Employees who choose to participate in training may have unobserved characteristics, such as higher motivation, better baseline skills, or greater adaptability, which could influence both their likelihood of participating in training and their ability to cope with new technologies. Therefore, the observed differences in effects might not be entirely causal and could be partially attributed to these unobserved factors.

4.3.2.2 Personnel Management

The previous sections showed that exposure to digital technologies influences job quality, training participation, and other employee-level outcomes. However, it is important to consider that the impact of these technologies on employees may also be shaped by their employer's organizational structure and management approach.

Management is ultimately responsible for making decisions regarding the adoption of new technologies and their integration into work processes. As a result, they play a crucial role in mitigating any potential negative effects of technologies on employees. One example of a management practice that could mitigate the adverse effects of digitalisation on job quality is conducting regular employee interviews and implementing mechanisms to incorporate feedback into future decision-making.

I incorporate these management practices as control variables in the regressions and estimate the effects using the same methodology employed for the previous analyses. If employee interviews, for instance, can alleviate the negative effects of digitalisation on job quality, their inclusion in the regressions should reduce the negative coefficients of basic digital technologies on working conditions.

However, incorporating controls for management practices does not eliminate the negative effects of basic digital technologies on working conditions and training participation, as shown in table 4.A.9. Similarly, the positive relationship identified between advanced digital technologies, working conditions, and training remains mostly unaffected by the inclusion of management controls. These findings suggest that while management practices such as employee interviews and feedback mechanisms are important, they are not sufficient to fully counteract the negative impacts of basic digital technologies. This underscores the need for a comprehensive approach that includes not only effective management practices but also targeted interventions aimed at supporting employees in adapting to new technologies.

4.4 Additional Results: Well-being and Health

In addition to the working conditions index, the concept of job quality also incorporates more subjective measures (Nikolova and Cnossen, 2020). In this context, well-being and job satisfaction are important factors (Clark, 2015). Also, low-quality jobs can be associated with worse health outcomes, especially if the work is physically demanding or is conducted in strenuous environmental conditions.

Tables 4.A.10 and 4.A.11 in the appendix present the results of regressions including further outcome variables related to job quality and individual well-being. These outcomes are job satisfaction, sick days, well-being, and work-life balance.

In line with the findings from the previous sections, the impacts of basic and advanced digital technologies on job satisfaction diverge. While not all estimates are statistically significant, panel A of table 4.A.10 illustrates that exposure to artificial intelligence or machine learning is associated with higher job satisfaction. In contrast, basic digital technologies are negatively associated with job satisfaction. On average, employees with high exposure to basic digital technologies or a high proportion of routine tasks report lower job satisfaction. Panel B of table 4.A.10 displays estimates related to sick days as a direct measure of an employee's health status, which is not self-reported but rather obtained from social security records. A similar pattern emerges as basic digital technologies correlate with a higher number of sick days, while increased exposure to advanced digital technologies is associated with a significantly lower number of sick days. The estimated coefficients are statistically significant at conventional levels, except for the routine task intensity measure. This finding further emphasizes the contrasting effects of basic and advanced digital technologies on employee well-being.

Lastly, table 4.A.11 presents results on self-reported well-being and work-life balance. These results are less consistent compared to earlier outcomes. For the well-being measure, none of the estimated coefficients reach statistical significance at the conventional levels. Considering self-reported work-life balance, exposure to basic digital technologies is negatively associated with it. Although exposure to machine learning also shows a negative relationship with work-life balance, the estimated coefficient is small and fails to reach statistical significance. In contrast, AI exposure has a positive and statistically significant association with this aspect of job quality.

In summary, these results support the main findings that exposure to basic digital technologies is related to lower job quality, while advanced digital technologies are connected to higher job quality. Furthermore, these findings extend to areas beyond strictly work-related measures, encompassing health and work-life balance.

4.5 Robustness Checks

To assess the robustness of the main results, I conduct a series of additional checks. First, I estimate the main regressions for different subsets of my sample. As not all employees are observed in all survey waves, the panel is unbalanced. To determine whether the effects depend on workers dropping out of the sample, I limit the sample to employees and establishments observed for at least two periods. The results are shown in table 4.A.12. The primary outcomes for working conditions and training do not change significantly.

Next, I further restrict the sample to include only employees observed in all four periods. This sample is significantly smaller, with around 3300 to 3400 observations. Table 4.A.13 shows the results. The estimated coefficient for computerization remains negative and statistically significant, while routine task intensity no longer has a significant effect. In contrast, coefficients for advanced digital technologies remain positive and mostly statistically significant, with magnitudes similar to those for the full sample.

For the next set of checks, I define the technology exposure variables as binary rather than continuous variables. I create variables that split technology exposure at the median such that the variable equals one if the occupational exposure is above the median and zero otherwise. This binary variable helps characterize higher exposure to the respective technologies.

Table 4.A.14 in the appendix shows the results. When estimating regressions with the above-median binary explanatory variables and working conditions and training as outcomes, the results largely confirm the initial set of regressions. Basic digital technology exposure above the median is negatively associated with working conditions and training participation. On the other hand, advanced digital technology exposure above the median is positively associated with better working conditions and higher training participation, with the estimated coefficients reaching statistical significance at the 1% level.

These robustness checks reinforce the main findings. The results indicate that the observed effects of digital technologies on working conditions and training participation are consistent across different sample restrictions and definitions of technology exposure. This adds confidence to the conclusion that basic digital technologies are generally associated with poorer working conditions and a lower propensity to participate in employer-provided training, while advanced digital technologies tend to improve working conditions and increase training participation.

4.6 Conclusion

This study provides new insights into the impact of digital technologies on job quality and participation in employer-provided training among incumbent workers in Germany. The findings highlight the differential effects of basic and advanced digital technologies, with advanced technologies generally being associated with improved working conditions and a higher likelihood of participating in employer-provided training. In contrast, basic digital technologies are associated with poorer outcomes.

Advanced technologies may enhance job quality by automating or assisting workers in complex tasks. These findings align with the task-based approach, which posits that advanced technologies can augment human labor in non-routine tasks (Brynjolfsson et al., 2018; Agrawal et al., 2019). Conversely, high exposure to basic digital technologies, such as computers and computer-controlled machines, correlates with poorer working conditions and reduced training participation. This can be explained by the automation of routine tasks and the resultant stress and job insecurity. These outcomes support the hypothesis that basic technologies primarily automate routine tasks (Autor et al., 2003; Acemoglu and Restrepo, 2019), adversely affecting job quality.

My results contribute to the existing literature by providing a nuanced understanding of how different types of digital technologies affect job quality. Previous studies have largely focused on the displacement effects of automation, while this study highlights the impacts of digital technologies on job quality. The positive association between advanced digital technologies and job quality aligns with findings from other studies on the health effects of AI (Giuntella et al., 2023; Arntz et al., 2024), while the negative impacts of basic digital technologies reflect concerns raised in the literature on automation and job displacement (Acemoglu et al., 2020).

The heterogeneous impacts of digital technologies across demographic groups suggest that male and older employees are particularly vulnerable to the adverse effects of basic digital technologies. This underscores the need for targeted interventions to support these workers, such as re-skilling programs and initiatives to promote lifelong learning. Furthermore, the role of ICT investments in amplifying the effects of digital technologies highlights the importance of strategic investment decisions by firms. Effective personnel management practices, such as regular employee interviews and feedback mechanisms, can mitigate some of the adverse impacts of digitalisation, suggesting that firms play an important role in shaping the outcomes of technological change.

This study has several limitations. First, the largely cross-sectional nature of the employee data limits the ability to draw causal inferences as selection into occupations and firms is difficult to address. Although a causal identification of digital technologies' effects on job quality and training is challenging in this empirical setting, the observed patterns align with studies using longitudinal data such as Arntz et al. (2024). Second, the measures of digital technology exposure may not capture all dimensions of technological change, such as the quality and implementation of these technologies. An extension of this work could involve an event study examining the introduction of new digital technology in a company and measuring employee-level outcomes in response to the introduction (Hirvonen et al., 2022; Genz et al., 2021; Bessen et al., 2019; Humlum and Vestergaard, 2024).

Navigating the adoption of new digital technologies poses challenges for both companies and employees. While successful adoption of new technologies enhances productivity, it can also alter job content and context, negatively affecting working conditions and job quality. Acknowledging this dual nature of digitalisation, both employers and employees could benefit from proactively addressing negative consequences by providing and participating in additional training and embracing employee-centric personnel management strategies. This proactive approach is crucial for ensuring the positive outcomes of digital technology adoption while mitigating potential downsides for employees.

4.A Additional Tables

Table 4.A.1: Top and Bottom 10 Occupations for Routine Task Intensity

Panel A: Highest Routine Task Intensity		
Occupation	Mean Exposure	Number of Employees
714 Office clerks and secretaries	0.965	921
721 Occupations in insurance and financial services	0.870	1,076
241 Occupations in metal-making	0.792	216
242 Occupations in metalworking	0.774	1,242
211 Occupations in mining and blasting engineering	0.746	248
292 Occupations in the production of foodstuffs, confectionery and tobacco	0.687	294
221 Occupations in plastic- and rubber-making and -processing	0.640	549
231 Technical occupations in paper-making and -processing and packaging	0.634	172
732 Occupations in public administration	0.624	91
715 Occupations in human resources management and personnel service	0.614	149
Panel B: Lowest Routine Task Intensity		
Occupation	Mean Exposure	Number of Employees
271 Occupations in technical research and development	0.000	504
711 Managing directors and executive board members	0.000	129
531 Occupations in physical security, protection and workplace safety	0.015	284
311 Occupations in construction scheduling, architecture	0.026	123
322 Occupations in civil engineering	0.026	114
321 Occupations in building construction	0.031	212
831 Occupations in education and social work	0.058	147
818 Occupations in pharmacy	0.047	96
821 Occupations in geriatric care	0.047	95
252 Technical occupations in the automotive, aeronautic, aerospace and ship building industries	0.043	455

Training participation is calculated for 3-digit occupations according to the kldb2010 classification.
Occupations with fewer than 20 employees are combined with occupations within the same 2-digit class for data protection reasons.

Table 4.A.2: Top and Bottom 10 Occupations for Computer Substitution Potential

Panel A: Highest Computer Substitution Potential		
Occupation	Mean Sub Potential	Number of Employees
241 Occupations in metal-making	0.933	216
245 Occupations in precision mechanics and tool making	0.863	239
242 Occupations in metalworking	0.845	1,242
211 Occupations in mining and blasting engineering	0.816	248
221 Occupations in plastic- and rubber-making and -processing	0.815	549
261 Occupations in mechatronics, automation and control technology	0.807	70
244 Occupations in metal constructing and welding	0.772	470
411 Occupations in mathematics and statistics	0.769	663
262 Technical occupations in energy technologies	0.751	612
263 Occupations in electrical engineering	0.748	466
Panel B: Lowest Computer Substitution Potential		
Occupation	Mean Sub Potential	Number of Employees
841 Teachers in schools of general education	0.061	110
818 Occupations in pharmacy	0.088	96
322 Occupations in civil engineering	0.094	114
531 Occupations in physical security, protection and workplace safety	0.104	284
831 Occupations in education and social work	0.117	147
321 Occupations in building construction	0.139	212
814 Occupations in human medicine and dentistry	0.150	303
921 Occupations in advertising and marketing	0.182	363
913 Occupations in the social sciences	0.214	181
821 Occupations in geriatric care	0.168	95

Training participation is calculated for 3-digit occupations according to the kldb2010 classification.
Occupations with fewer than 20 employees are combined with occupations within the same 2-digit class for data protection reasons.

Table 4.A.3: Top and Bottom 10 Occupations for AI Exposure

Panel A: Highest AI Exposure		
Occupation	Mean AI Exposure	Number of Employees
722 Occupations in accounting, controlling and auditing	0.934	506
715 Occupations in human resources management and personnel service	0.897	149
714 Office clerks and secretaries	0.852	921
713 Occupations in business organisation and strategy	0.851	1,447
913 Occupations in the social sciences	0.849	181
311 Occupations in construction scheduling, architecture	0.823	123
611 Occupations in purchasing and sales	0.799	1,033
431 Occupations in computer science	0.794	65
921 Occupations in advertising and marketing	0.785	363
732 Occupations in public administration	0.771	91
Panel B: Lowest AI Exposure		
Occupation	Mean AI Exposure	Number of Employees
541 Occupations in cleaning services	0.083	307
244 Occupations in metal constructing and welding	0.171	470
221 Occupations in plastic- and rubber-making and -processing	0.254	549
241 Occupations in metal-making	0.281	216
211 Occupations in mining and blasting engineering	0.285	248
292 Occupations in the production of foodstuffs, confectionery and tobacco	0.327	294
242 Occupations in metalworking	0.319	1,242
322 Occupations in civil engineering	0.214	114
321 Occupations in building construction	0.219	212
341 Occupations in building services engineering	0.130	104

Training participation is calculated for 3-digit occupations according to the kldb2010 classification.
Occupations with fewer than 20 employees are combined with occupations within the same 2-digit class for data protection reasons.

Table 4.A.4: Top and Bottom 10 Occupations for Machine Learning Suitability

Panel A: Highest ML Suitability		
Occupation	Mean ML Suitability	Number of Employees
722 Occupations in accounting, controlling and auditing	0.899	506
272 Draftspersons, technical designers, and model makers	0.898	481
714 Office clerks and secretaries	0.877	921
721 Occupations in insurance and financial services	0.881	1,076
622 Sales occupations clothing, electronic devices, furniture, motor vehicles	0.833	185
623 Sales occupations selling foodstuffs	0.833	130
611 Occupations in purchasing and sales	0.804	1,033
732 Occupations in public administration	0.795	91
621 Sales occupations in retail trade (without product specialisation)	0.793	210
921 Occupations in advertising and marketing	0.770	363
Panel B: Lowest ML Suitability		
Occupation	Mean ML Suitability	Number of Employees
322 Occupations in civil engineering	0.425	114
321 Occupations in building construction	0.461	212
818 Occupations in pharmacy	0.475	96
341 Occupations in building services engineering	0.516	104
541 Occupations in cleaning services	0.513	307
525 Drivers and operators of construction and transportation vehicles	0.539	250
343 Occupations in building services and waste disposal	0.532	215
821 Occupations in geriatric care	0.557	95
311 Occupations in construction scheduling, architecture	0.565	123
111 Occupations in farming	0.572	46

Training participation is calculated for 3-digit occupations according to the kldb2010 classification.
Occupations with fewer than 20 employees are combined with occupations within the same 2-digit class for data protection reasons.

Table 4.A.5: Occupations by Average Training Participation

Occupation	Mean Training Participation	N Training	N No Training	N Total
Panel A: Highest Average Training Participation				
814 Occupations in human medicine and dentistry	0.708	213	88	303
818 Occupations in pharmacy	0.708	68	28	96
831 Occupations in education and social work	0.721	106	41	147
715 Occupations in human resources management and personnel service	0.597	89	60	149
271 Occupations in technical research and development	0.599	300	201	504
841 Teachers in schools of general education	0.670	73	36	110
821 Occupations in geriatric care	0.632	60	35	95
721 Occupations in insurance and financial services	0.568	611	465	1,076
311 Occupations in construction scheduling, architecture	0.545	67	56	123
711 Managing directors and executive board members	0.555	71	57	129
Panel B: Lowest Average Training Participation				
Occupation	Mean Training Participation	N Training	N No Training	N Total
541 Occupations in cleaning services	0.085	26	281	307
221 Occupations in plastic- and rubber-making and -processing	0.184	101	448	549
242 Occupations in metalworking	0.228	283	959	1,242
631 Occupations in tourism and the sports (and fitness) industry	0.228	34	115	149
511 Technical occupations in railway, aircraft and ship operation	0.220	316	1,120	1,437
292 Occupations in the production of foodstuffs, confectionery and tobacco	0.204	60	234	294
321 Occupations in building construction	0.255	54	158	212
525 Drivers and operators of construction and transportation vehicles	0.248	62	188	250
343 Occupations in building services and waste disposal	0.252	54	160	215
231 Technical occupations in paper-making and -processing and packaging	0.263	45	126	172

Training participation is calculated for 3-digit occupations according to the kldb2010 classification.
Occupations with fewer than 20 employees are combined with occupations within the same 2-digit class for data protection reasons.

Table 4.A.6: Digitalisation, Working Conditions and Training - by Age

	(18-29)	(30-49)	(50-67)	(18-29)	(30-49)	(50-67)	(18-29)	(30-49)	(50-67)	(18-29)	(30-49)	(50-67)
Panel A: Working Conditions												
Basic digital technologies:												
Routine Task Intensity	-0.342	-0.272	-0.955***									
	(0.662)	(0.305)	(0.361)									
Computerization				-1.386	-2.479***	-2.638***						
				(1.057)	(0.333)	(0.331)						
Advanced digital technologies:												
AI Exposure							2.800*	4.941***	4.194***			
							(1.590)	(0.430)	(0.302)			
Machine Learning Suitability										4.982***	5.386***	2.543***
										(1.357)	(0.522)	(0.851)
Individual-level Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.532	0.372	0.341	0.534	0.387	0.354	0.547	0.434	0.385	0.546	0.400	0.342
Observations	1644	9001	10329	1644	9001	10329	1644	9001	10329	1644	9001	10329
Panel B: Training Participation												
Basic digital technologies:												
Routine Task Intensity	0.123	-0.128***	-0.065									
	(0.088)	(0.043)	(0.042)									
Computerization				-0.162	-0.255***	-0.222***						
				(0.181)	(0.057)	(0.059)						
Advanced digital technologies:												
AI Exposure							0.055	0.276***	0.220***			
							(0.276)	(0.057)	(0.041)			
Machine Learning Suitability										0.701***	-0.033	0.073
										(0.233)	(0.082)	(0.125)
Individual-level Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.463	0.283	0.251	0.461	0.285	0.256	0.460	0.287	0.256	0.472	0.278	0.250
Observations	1645	9010	10348	1645	9010	10348	1645	9010	10348	1645	9010	10348

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Control variables include education, gender, qualification, wage, establishment size, leadership, and full-time employment. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A.7: Digitalisation, Working Conditions and Training - by Gender

	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
Panel A: Working Conditions								
Basic digital technologies:								
Routine Task Intensity	0.929*	-1.137***						
	(0.535)	(0.272)						
Computerization			-0.655	-3.005***				
			(0.483)	(0.277)				
Advanced digital technologies:								
AI Exposure					4.556***	4.181***		
					(0.592)	(0.338)		
Machine Learning Suitability							6.018***	3.269***
							(0.907)	(0.600)
Individual-level Controls	✓	✓	✓	✓	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.393	0.334	0.389	0.350	0.438	0.374	0.420	0.336
Observations	5978	14996	5978	14996	5978	14996	5978	14996
Panel B: Training Participation								
Basic digital technologies:								
Routine Task Intensity	-0.024	-0.124***						
	(0.042)	(0.033)						
Computerization			-0.250***	-0.223***				
			(0.073)	(0.044)				
Advanced digital technologies:								
AI Exposure					0.206**	0.248***		
					(0.102)	(0.057)		
Machine Learning Suitability							-0.024	0.090
							(0.126)	(0.081)
Individual-level Controls	✓	✓	✓	✓	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.392	0.225	0.397	0.226	0.396	0.228	0.392	0.221
Observations	5987	15016	5987	15016	5987	15016	5987	15016

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Control variables include age, gender, education, qualification, wage, establishment size, leadership, and full-time employment. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A.8: Digitalisation and working conditions - conditional on training

	(1) No Training	(2) Training	(3) No training	(4) Training	(5) No training	(6) Training	(7) No training	(8) Training
Basic digital technologies:								
Routine Task Intensity	-0.652**	-0.022						
	(0.276)	(0.264)						
Computerization			-2.761***	-1.889***				
			(0.348)	(0.284)				
Advanced digital technologies:								
AI Exposure					4.628***	3.850***		
					(0.359)	(0.595)		
Machine Learning Suitability							4.025***	4.266***
							(0.538)	(0.827)
Individual-level Controls	✓	✓	✓	✓	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.314	0.328	0.328	0.339	0.367	0.376	0.326	0.350
Observations	12579	8383	12579	8383	12579	8383	12579	8383

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Control variables include age, education, qualification, wage, establishment size, leadership, and full-time employment. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A.9: Digitalisation, Working Conditions and Training - Management Controls

	(1)	(2)	(3)	(4)
Panel A: Working Conditions				
Basic digital technologies:				
Routine Task Intensity	-0.386*			
	(0.204)			
Computerization		-2.399***		
		(0.246)		
Advanced digital technologies:				
AI Exposure			4.294***	
			(0.323)	
Machine Learning Suitability				4.106***
				(0.437)
Individual-level Controls	✓	✓	✓	✓
Management Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.321	0.335	0.374	0.338
Observations	20866	20866	20866	20866
Panel B: Training Participation				
Basic digital technologies:				
Routine Task Intensity	-0.060			
	(0.036)			
Computerization		-0.201***		
		(0.038)		
Advanced digital technologies:				
AI Exposure			0.194***	
			(0.039)	
Machine Learning Suitability				0.062
				(0.068)
Individual-level Controls	✓	✓	✓	✓
Management controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.237	0.240	0.241	0.236
Observations	20895	20895	20895	20895

Notes: All models estimated are OLS with establishment and year fixed effects included. Control variables include age, education, qualification, wage, establishment size, leadership, and full-time employment. Management controls include employee interviews, performance pay and a measure for teamwork. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A.10: Digitalisation, Job Satisfaction and Sick Days

	(1)	(2)	(3)	(4)
Panel A: Job Satisfaction				
Basic digital technologies:				
Routine Task Intensity	-0.160*			
	(0.090)			
Computerization		-0.213		
		(0.163)		
Advanced digital technologies:				
AI Exposure			0.295**	
			(0.145)	
Machine Learning Suitability				0.097
				(0.201)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.150	0.149	0.150	0.149
Observations	21008	21008	21008	21008
Panel B: Sick Days				
Basic digital technologies:				
Routine Task Intensity	3.017			
	(2.057)			
Computerization		6.060**		
		(2.457)		
Advanced digital technologies:				
AI Exposure			-11.405***	
			(2.414)	
Machine Learning Suitability				-6.647***
				(2.030)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.187	0.188	0.195	0.187
Observations	14862	14862	14862	14862

Notes: All models estimated are OLS with establishment and year fixed effects included. The job satisfaction index ranges from 0 to 10. Control variables include age, education, qualification, wage, establishment size, leadership, and full-time employment. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A.11: Digitalisation, Well-being and Work-life Balance

	(1)	(2)	(3)	(4)
Panel A: Well-being				
Basic digital technologies:				
Routine Task Intensity	0.255			
	(0.337)			
Computerization		-0.088		
		(0.390)		
Advanced digital technologies:				
AI Exposure			-0.015	
			(0.474)	
Machine Learning Suitability				0.110
				(0.532)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.130	0.130	0.130	0.130
Observations	20897	20897	20897	20897
Panel B: Work-life Balance				
Basic digital technologies:				
Routine Task Intensity	-0.203**			
	(0.086)			
Computerization		-0.426**		
		(0.191)		
Advanced digital technologies:				
AI Exposure			0.311**	
			(0.153)	
Machine Learning Suitability				-0.101
				(0.166)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.165	0.166	0.165	0.163
Observations	9613	9613	9613	9613

Notes: All models estimated are OLS with establishment and year fixed effects included. The well-being index ranges from 5 to 30. The work-life balance index ranges from 1 to 5. Control variables include age, gender, education, qualification, wage, establishment size, leadership, and full-time employment. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A.12: R1: Working Conditions and Training - Employees in minimum two waves

	(1)	(2)	(3)	(4)
Panel A: Working Conditions				
Routine Task Intensity	-0.467*			
	(0.272)			
Computerization		-2.386***		
		(0.341)		
Advanced digital technologies:				
AI Exposure			4.513***	
			(0.448)	
Machine Learning Suitability				4.315***
				(0.523)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.333	0.348	0.391	0.347
Observations	14730	14957	14413	14365
Panel B: Training Participation				
Basic digital technologies:				
Routine Task Intensity	-0.071			
	(0.053)			
Computerization		-0.254***		
		(0.053)		
Advanced digital technologies:				
AI Exposure			0.229***	
			(0.061)	
Machine Learning Suitability				0.201**
				(0.085)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.221	0.229	0.230	0.222
Observations	14747	14974	14431	14382

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Employees are observed in two or more survey waves. Control variables include age, education, qualification, wage, establishment size, leadership, and full-time employment. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A.13: R2: Working Conditions and Training - Employees in four waves

	(1)	(2)	(3)	(4)
Panel A: Working Conditions				
Basic digital technologies:				
Routine Task Intensity	0.268			
	(0.574)			
Computerization		-2.079***		
		(0.582)		
Advanced digital technologies:				
AI Exposure			4.565***	
			(0.942)	
Machine Learning Suitability				3.832***
				(1.267)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.509	0.518	0.546	0.513
Observations	3412	3445	3292	3279
Panel B: Training Participation				
Basic digital technologies:				
Routine Task Intensity	-0.080			
	(0.068)			
Computerization		-0.255**		
		(0.108)		
Advanced digital technologies:				
AI Exposure			0.319***	
			(0.096)	
Machine Learning Suitability				0.004
				(0.142)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.301	0.305	0.308	0.308
Observations	3419	3452	3300	3286

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Employees are observed in all four survey waves. Control variables include age, education, qualification, wage, establishment size, leadership, and full-time employment. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A.14: R3: Working Conditions and Training - Exposure above median

	(1)	(2)	(3)	(4)
Panel A: Working Conditions				
Basic digital technologies:				
RTI >50pct	-0.192			
	(0.142)			
Computerization >50pct		-1.220***		
		(0.114)		
Advanced digital technologies:				
AI Exposure >50pct			2.085***	
			(0.201)	
ML Suitability >50pct				0.803***
				(0.133)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.293	0.313	0.346	0.303
Observations	22939	22939	22939	22939
Panel B: Training Participation				
Basic digital technologies:				
RTI >50pct	-0.047*			
	(0.026)			
Computerization >50pct		-0.098***		
		(0.021)		
Advanced digital technologies:				
AI Exposure >50pct			0.119***	
			(0.031)	
ML Suitability >50pct				0.037*
				(0.021)
Individual-level Controls	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.217	0.222	0.223	0.217
Observations	22970	22970	22970	22970

Notes: All models estimated are OLS with establishment and year fixed effects included. The working conditions index ranges from 5 to 25. Control variables include age, education, qualification, wage, establishment size, leadership, and full-time employment. LPP-ADIAB panel weights are applied. Standard errors are clustered at establishment level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Bibliography

Abowd, John, Francis Kramarz, and David Margolis (1999) "High Wage Workers and High Wage Firms," *Econometrica*, 67 (2), 251–334.

Acemoglu, Daron, U. Akcigit, and M. Celik (2014) "Young, Restless and Creative: Openness to Disruption and Creative Innovations," *NBER Working Paper No. 19894*.

Acemoglu, Daron and David Autor (2011) "Skills, Tasks and Technologies: Implications for Employment and Earnings," in *Handbook of Labor Economics*, Chap. 12, volume 4, 1043–1171: North Holland: Elsevier.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo (2022) "Artificial Intelligence and Jobs: Evidence from Online Vacancies," *Journal of Labor Economics*, 40 (S1), S293–S340.

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo (2020) "Competing with Robots: Firm-Level Evidence from France," *AEA Papers and Proceedings*, 110, 383–88.

Acemoglu, Daron and Pascual Restrepo (2018) "Low-Skill and High-Skill Automation," *Journal of Human Capital*, 12 (2), 204–232.

——— (2019) "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, 33 (2), 3–30.

——— (2020) "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 128 (6), 2188–2244.

Agrawal, Ajay, Joshua Gans, and Avi Goldfarb (2019) "Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction," *Journal of Economic Perspectives*, 33 (2), 31–50.

Agrawal, Ajay, Joshua S. Gans, and Avi Goldfarb (2023) "Do we want less automation?" *Science*, 381 (6654), 155–158.

Albanesi, Stefania, António Dias da Silva, Juan Jimeno, Ana Lamo, and Alena Wabitsch (2023) "New Technologies and Jobs in Europe," *IZA Discussion Paper No. 16227*.

Alderucci, D., L. Branstetter, E. Hovy, A. Runge, and N. Zolas (2021) "Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata," *mimeo*.

Alekseeva, Liudmila, José Azar, Mireia Giné, Sampsa Samila, and Bledi Taska (2021) "The demand for AI skills in the labor market," *Labour Economics*, 71, 102002.

Arntz, Melanie, Sebastian Findeisen, Stephan Maurer, and Oliver Schlenker (2024) "Are we yet sick of new technologies? The unequal health effects of digitalization," *CEPR Discussion Paper No. 18913*.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn (2017) "Revisiting the Risk of Automation," *Economics Letters*, 159, 157 – 160.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum (2018) "New technologies and the labor market," *Journal of Monetary Economics*, 97, 48–67.

Autor, David, Caroline Chin, Anna Salomons, and Bryan Seegmiller (2024) "New Frontiers: The Origins and Content of New Work, 1940–2018," *The Quarterly Journal of Economics*.

Autor, David and David Dorn (2013) "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103 (5), 1553–1597.

Autor, David, David Dorn, and Gordon Hanson (2013) "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103 (6), 2121–68.

Autor, David, Frank Levy, and Richard Murnane (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118 (4), 1279–333.

Ayyagari, Grover, and Purvis (2011) "Technostress: Technological Antecedents and Implications," *MIS Quarterly*, 35 (4), 831.

Bakker, Arnold B. and Evangelia Demerouti (2007) "The Job Demands-Resources model: state of the art," *Journal of Managerial Psychology*, 22 (3), 309–328.

Bartel, A., C. Ichniowski, and K. Shaw (2007) "How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills," *The Quarterly Journal of Economics*, 122 (4), 1721–1758.

Bartik, Timothy (1993) "Who Benefits from Local Job Growth: Migrants or the Original Residents?," *Regional Studies*, 27 (4), 297–311.

Baruffaldi, Stefano, Brigitte van Beuzekom, Hélène Dernis, Dietmar Harhoff, Nandan Rao, David Rosenfeld, and Mariagrazia Squicciarini (2020) "Identifying and Measuring Developments in Artificial Intelligence," *OECD Science, Technology and Industry Working Papers*.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen (2018) "Who Becomes an Inventor in America? The Importance of Exposure to Innovation," *The Quarterly Journal of Economics*, 134 (2), 647–713.

Benmelech, Efraim and Michal Zator (2022) "Robots and Firm Investment," *NBER Working Paper No. 29676.*

Bessen, James (2016) "How Computer Automation Affects Occupations: Technology, Jobs, and Skills," *Boston University School of Law, Law and Economics Research Paper* (15-49).

Bessen, James E., Maarten Goos, Anna Salomons, and Wiljan Van den Berge (2019) "Automatic Reaction - What Happens to Workers at Firms that Automate?" *SSRN Electronic Journal.*

Bessen, James and Robert Hunt (2007) "An Empirical Look at Software Patents," *Journal of Economics and Management Strategy*, 16 (1), 157–189.

Bloom, Nicholas, Luis Garicano, Raffaella Sadun, and John van Reenen (2014) "The Distinct Effects of Information Technology and Communication Technology on Firm Organization," *Management Science*, 60 (12), 2859–2885.

Bonfiglioli, Alessandra, Rosario Crinò, Harald Fadinger, and Gino Gancia (2020) "Robot Imports and Firm-Level Outcomes," *CESifo Working Paper No. 8741.*

Bonfiglioli, Alessandra, Gino Gancia, Ioannis Papadakis, and Rosario Crinò (2023) "Artificial Intelligence and Jobs: Evidence from US Commuting Zones," *CESifo Working Paper Series 10685.*

Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2021) "Quasi-Experimental Shift-Share Research Designs," *The Review of Economic Studies*, 89 (1), 181–213.

Bresnahan, T., E. Brynjolfsson, and L. Hitt (2002) "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *Quarterly Journal of Economics*, 117 (1), 339–376.

Broszeit, Sandra, Corinna Frodermann, Philipp Grunau, Stefanie Wolter et al. (2017) "LPP-Linked Personnel Panel survey data linked with administrative data of the IAB (LPP-ADIAB) 1975-2014," *FDZ-Datenreport*, 3, 2017.

Brunello, Giorgio, Désirée Rückert, Christoph Weiss, and Patricia Wruuck (2023) "Advanced Digital Technologies and Investment in Employee Training: Complements or Substitutes?" *EIB Working Papers 2023/01.*

Brynjolfsson, Erik and Andrew McAfee (2014) *The Second Machine Age*: W.W. Norton & Co.

Brynjolfsson, Erik, Tom Mitchell, and Daniel Rock (2018) "What Can Machines Learn, and What Does It Mean for Occupations and the Economy?," *AEA Papers and Proceedings*, 108, 43–47.

Bryson, Alex, John Forth, and Lucy Stokes (2017) "Does employees' subjective well-being affect workplace performance?" *Human Relations*, 70 (8), 1017–1037.

Caroli, Eve and John van Reenen (2001) "Skill-Biased Organizational Change? Evidence from a Panel of British and French Establishments," *The Quarterly Journal of Economics*, 116 (4), 1449–1492.

Clark, Andrew (2015) "What makes a good job? Job quality and job satisfaction," *IZA World of Labor.*

Consoli, Davide, Giovanni Marin, Francesco Rentocchini, and Francesco Vona (2023) "Routinization, within-occupation task changes and long-run employment dynamics," *Research Policy*, 52 (1), 104658.

Cortes, Guido Matias (2016) "Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data," *Journal of Labor Economics*, 34 (1), 63–105.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner (2021) "The Adjustment of Labor Markets to Robots," *Journal of the European Economic Association*, 19 (6), 3104–3153.

Dechezleprêtre, Antoine, David Hémous, Morten Olsen, and Carlo Zanella (2020) "Automating Labor: Evidence from Firm-Level Patent Data," *CEPR Discussion Paper No. 14249.*

Demerouti, Evangelia, Arnold B. Bakker, Friedhelm Nachreiner, and Wilmar B. Schaufeli (2001) "The job demands-resources model of burnout.," *Journal of Applied Psychology*, 86 (3), 499–512.

Dengler, Katharina and Stefanie Gundert (2021) "Digital Transformation and Subjective Job Insecurity in Germany," *European Sociological Review*, 37 (5), 799–817.

Dengler, Katharina and Britta Matthes (2018) "The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany," *Technological Forecasting and Social Change*, 137, 304 – 316.

DiMaria, Charles Henri, Chiara Peroni, and Francesco Sarracino (2019) "Happiness Matters: Productivity Gains from Subjective Well-Being," *Journal of Happiness Studies*, 21 (1), 139–160.

Dixon, Jay, Bryan Hong, and Lynn Wu (2021) "The Robot Revolution: Managerial and Employment Consequences for Firms," *Management Science*, 67 (9), 5586–5605.

Dorner, Matthias and Dietmar Harhoff (2018) "A novel technology-industry concordance table based on linked inventor establishment data," *Research Policy*, 47, 768–781.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock (2023) "GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models."

Eurofound (2022) *Working conditions in the time of COVID-19: implications for the future.*: European Publications Office.

Felten, Edward, Manav Raj, and Robert Seamans (2018) "A Method to Link Advances in Artificial Intelligence to Occupational Abilities," *AEA Papers and Proceedings*, 108, 54–57.

——— (2019) "The Variable Impact of Artificial Intelligence on Labor: The Role of Complementary Skills and Technologies," *SSRN Electronic Journal*.

Fitzenberger, Bernd, Aderonke Osikominu, and Robert Völter (2005) " Imputation Rules to Improve the Education Variable in the IAB Employment Subsample," *FDZ-Methodenreport 03*.

Frey, Carl and Michael Osborne (2017) "The Future of Employment: How Susceptible are Jobs to Computerisation?," *Technological Forecasting and Social Change*, 114 (C), 254–280.

Ganzer, Andreas, Lisa Schmidtlein, Jens Stegmaier, and Stefanie Wolter (2020) "Establishment History Panel 1975-2019," *FDZ-Datenreport 16*.

Gartner, Hermann (2005) "The Imputation of Wages above the Contribution Limit with the German IAB Employment Sample," *FDZ-Methodenreport 02*.

Gathmann, Christina and Felix Grimm (2023) "Labor Market Effects of AI and Robotics," *mimeo*.

Gathmann, Christina and Uta Schönberg (2010) "How General Is Human Capital? A Task-Based Approach," *Journal of Labor Economics*, 28 (1), 1–49.

Genz, Sabrina, Terry Gregory, Markus Janser, Florian Lehmer, and Britta Matthes (2021) "How do Workers adjust when Firms Adopt New Technologies," *IZA DP No. 14626*.

Gerdiken, Elena, Max Reinwald, and Florian Kunze (2021) "Outcomes of Technostress at Work: A Meta-Analysis," *Academy of Management Proceedings*, 2021 (1), 11807.

Gerten, Elisa, Michael Beckmann, and Lutz Bellmann (2019) "Controlling Working Crowds: The Impact of Digitalization on Worker Autonomy and Monitoring Across Hierarchical Levels," *Journal of Economics and Statistics (Jahrbuecher fuer Nationaloekonomie und Statistik)*, 239 (3), 441–481.

Gihleb, Rania, Osea Giuntella, Luca Stella, and Tianyi Wang (2022) "Industrial robots, Workers' safety, and health," *Labour Economics*, 78, 102205.

Giuntella, Osea, Johannes König, and Luca Stella (2023) "Artificial Intelligence and Workers' Well-Being," *IZA Discussion Paper No. 16485*.

Goldschlag, Nathan, Travis Lybbert, and Nikolas Zolas (2016) "An Algorithmic Links with Probabilitiess Crosswalk for USPC and CPC Patent Classifications with an Application Towards Industrial Technology Composition," *SSRN Electronic Journal*.

——— (2019) "Tracking the Technological Composition of Industries with Algorithmic Patent Concordances," *Economics of Innovation and New Technology*.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2018) "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 110 (24408), 2586–2624.

Goos, Maarten, Alan Manning, and Anna Salomons (2009) "Job Polarization in Europe," *American Economic Review*, 99 (2), 58–63.

——— (2014) "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104 (8), 2509–2526.

Graetz, Georg and Guy Michaels (2018) "Robots at Work," *The Review of Economics and Statistics*, 100 (5), 753–768.

Green, Francis (2012) "Employee Involvement, Technology and Evolution in Job Skills: A Task-Based Analysis," *ILR Review*, 65 (1), 36–67.

Gregory, Terry, Anna Salomons, and Ulrich Zierahn (2019) "Racing With or Against the Machine? Evidence from Europe," IZA Discussion Papers 12063.

Griliches, Zvi (1990) "Patent Statistics as Economic Indicators: A Survey," *Journal of Economic Literature*, 28 (4), 1661–1707.

Gunadi, Christian and Hanbyul Ryu (2021) "Does the rise of robotic technology make people healthier?" *Health Economics*, 30 (9), 2047–2062.

Haepp, Tobias (2021) "New technologies and employee well-being: the role of training provision," *Applied Economics Letters*, 1–6.

Hall, Anja, Lena Huenefeld, and Daniela Rohrbach-Schmidt (2020) "BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2018. $VT_1.0$.″

Hall, Anja, Anke Siefer, and Michael Tiemann (2014) "BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2012. $VT_1.0$.″

Hall, Anja and Michael Tiemann (2009) "BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2006. $VT_1.0$.″

Hall, B., A. Jaffe, and M. Trajtenberg (2001) "The NBER Patent Citation Data File: Lessons, Insights and Methodologial Tools," *NBER Working Paper No. 8498.*

Hirvonen, Johannes, Aapo Stenhammar, and Joonas Tuhkuri (2022) "New Evidence on the Effect of Technology on Employment and Skill Demand," (93).

Humlum, A. (2019) "Robot adoption and labor market dynamics,"Technical report.

Humlum, Anders and Emilie Vestergaard (2024) "The Adoption of ChatGPT," *SSRN Electronic Journal.*

International Federation of Robotics (2020) "World Robotics Industrial Robots and Service Robots,"Technical report.

Jaffe, Adam, Manuel Trajtenberg, and Rebecca Henderson (1993) "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *Quarterly Journal of Economics*, 108 (3), 577–598.

Jones, Benjamin F and Xiaojie Liu (2024) "A framework for economic growth with capital-embodied technical change," *American Economic Review*, 114 (5), 1448–1487.

de Jonge, Jan, Hans Bosma, Richard Peter, and Johannes Siegrist (2000) "Job strain, effort-reward imbalance and employee well-being: a large-scale cross-sectional study," *Social Science & Medicine*, 50 (9), 1317–1327.

Judge, Timothy A., Carl J. Thoresen, Joyce E. Bono, and Gregory K. Patton (2001) "The job satisfaction–job performance relationship: A qualitative and quantitative review.," *Psychological Bulletin*, 127 (3), 376–407.

Kampkötter, Patrick, Jens Mohrenweiser, Dirk Sliwka, Susanne Steffes, and Stefanie Wolter (2016) "Measuring the use of human resources practices and employee attitudes," *Evidence-based HRM: a Global Forum for Empirical Scholarship*, 4 (2), 94–115.

Karasek, Robert A. (1979) "Job Demands, Job Decision Latitude, and Mental Strain: Implications for Job Redesign," *Administrative Science Quarterly*, 24 (2), 285.

Kessler, Sarah (2023) "AI is Changing Jobs and Work," *The New York Times*, `https://www.nytimes.com/2023/06/10/business/ai-jobs-work.html`, Accessed: 2024-05-24.

Koch, Michael, Ilya Manuylov, and Marcel Smolka (2021) "Robots and Firms," *The Economic Journal*, 131 (638), 2553–2584.

Kortum, Samuel and Jonathan Putnam (1997) "Assigning Patents to Industries: Tests of the Yale Technology Concordance," *Economic Systems Research*, 9 (2), 161–176.

Lindbeck, Assar and Dennis J. Snower (2000) "Multitask Learning and the Reorganization of Work: From Tayloristic to Holistic Organization," *Journal of Labor Economics*, 18 (3), 353–376.

Lukowski, Felix, Myriam Baum, and Sabine Mohr (2020) "Technology, tasks and training – evidence on the provision of employer-provided training in times of technological change in Germany," *Studies in Continuing Education*, 43 (2), 174–195.

Lybbert, Travis and Nikolas Zolas (2014) "Getting Patents and Economic Data to Speak to each other: An 'Algorithmic Links with Probabilities' Approach for joint Analyses of Patenting and Economic Activity," *Research Policy*, 43, 530–542.

Mann, Katja and Lukas Püttmann (2023) "Benign Effects of Automation: New Evidence from Patent Texts," *Review of Economics and Statistics*, 105 (3), 562–579.

Marr, Bernard (2023) "A Short History of ChatGPT: How We Got to Where We Are Today," *Forbes*, `https://www.forbes.com/sites/bernardmarr/2023/05/19/a-short-history-of-chatgpt-how-we-got-to-where-we-are-today/?sh=3f890236674f`.

Martin, Ludivine and Laetitia Hauret (2022) "Digitalization, Job Quality, and Subjective Well-being," in *Handbook of Labor, Human Resources and Population Economics*, 1–41: Springer International Publishing.

Mihaylov, Emil and Kea Gartje Tijdens (2019) "Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations," *SSRN Electronic Journal*.

Montobbio, Fabio, Jacopo Staccioli, Maria Enrica Virgillito, and Marco Vivarelli (2022) "Robots and the origin of their labour-saving impact," *Technological Forecasting and Social Change*, 174, 121122.

Moser, Petra (2005) "How Do Patent Laws Influence Innovation? Evidence from Nineteenth-Century World's Fairs," *American Economic Review*, 95 (4), 1214–1236.

——— (2013) "Patents and Innovation: Evidence from Economic History," *Journal of Economic Perspectives*, 27 (1), 23–44.

Nazareno, Luísa and Daniel S. Schiff (2021) "The impact of automation and artificial intelligence on worker well-being," *Technology in Society*, 67, 101679.

Nikolova, Milena and Femke Cnossen (2020) "What makes work meaningful and why economists should care about it," *Labour Economics*, 65, 101847.

OECD (2023) *OECD Employment Outlook 2023*: OECD.

Oswald, Andrew J., Eugenio Proto, and Daniel Sgroi (2015) "Happiness and Productivity," *Journal of Labor Economics*, 33 (4), 789–822.

Pratt, Gill (2015) "Is a Cambrian Explosion Coming for Robotics?," *Journal of Economic Perspectives*, 29 (3), 51–60.

Prytkova, Ekaterina, Fabien Petit, Deyu Li, Sugat Chaturvedi, and Tommaso Ciarli (2024) "The Employment Impact of Emerging Digital Technologies," *CESifo Working Paper No. 10955*.

Ragu-Nathan, T. S., Monideepa Tarafdar, Bhanu S. Ragu-Nathan, and Qiang Tu (2008) "The Consequences of Technostress for End Users in Organizations: Conceptual Development and Empirical Validation," *Information Systems Research*, 19 (4), 417–433.

Romer, Paul M (1990) "Endogenous Technological Change," *Journal of Political Economy*, 98 (5, Part 2), S71–S102.

Ruf, K., J. Mackeben, P. Grunau, and S. Wolter (2019) "A unique Employer-Employee Study: the Linked Personnel Panel (LPP) – Design, Extensions and Research Potential," *Jahrbücher für Nationalökonomie und Statistik*, 240 (1), 133–145.

Schmoch, Ulrich (2008) "Concept of a Technology Classification for Country Comparisons," *World Intellectual Property Organization*.

Schwab, Klaus (2016) “The Fourth Industrial Revolution: What It Means, How To Respond,” *Foreign Affairs*, 94.

Schwabe, Henrik and Fulvio Castellacci (2020) “Automation, workers’ skills and job satisfaction,” *PLOS ONE*, 15 (11).

Silverman, Brian S (2002) *Technological Resources and the Logic of Corporate Diversification*: Routledge.

Sorgner, Alina (2017) “The Automation of Jobs: A Threat for Employment or a Source of New Entrepreneurial Opportunities?” *Foresight and STI Governance*, 11 (3), 37–48.

Spitz-Oener, Alexandra (2006) “Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure,” *Journal of Labor Economics*, 24 (2), 235–270.

Tarafdar, Monideepa, Qiang Tu, Bhanu S. Ragu-Nathan, and T. S. Ragu-Nathan (2007) “The Impact of Technostress on Role Stress and Productivity,” *Journal of Management Information Systems*, 24 (1), 301–328.

Tolan, Songül, Annarosa Pesole, Fernando Martínez-Plumed, Enrique Fernández-Macías, José Hernández-Orallo, and Emilia Gómez (2021) “Measuring the Occupational Impact of AI: Tasks, Cognitive Abilities and AI Benchmarks,” *Journal of Artificial Intelligence Research*, 71, 191–236.

Webb, Michael (2020) “The Impact of Artificial Intelligence on the Labor Market,” *Stanford University*.

World Intellectual Property Organization (2019) “WIPO Technology Trends 2019: Artificial Intelligence,” Geneva.

Wotschack, Philip (2020) “Drivers of training participation in low skilled jobs: the role of ‘voice’, technology, innovation and labor shortages in German companies,” *International Journal of Training and Development*, 24 (3), 245–264.