Advanced Technology Adoption: Determinants and Labor Market Effects of Robot Use

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Table of Contents

List of Tables

List of Figures

Chapter 1

Robot Adoption at German Plants[1]

1.1 Introduction

The recent advances in automation technology, robotics in particular, have sparked a heated debate over the future of labor and human society at large. The ongoing process of robotization may engender profound impacts on various segments of the labor market. Given the far-reaching implications of robots, it is thus very important to understand the scale and scope of robot use and characteristics of robot users. However, the main challenge is the limited availability of robot data at the microeconomic level (Raj and Seamans, 2018). Due to the data constraint, the bulk of the existing literature relies on cross-country industry-level data from the International Federation of Robotics (IFR). The lack of micro-level robot data makes it difficult to paint a comprehensive picture of robotization in industrial settings, and perhaps more importantly, to assess how within-industry firm level heterogeneity manifests itself in robot use and adoption.

In this paper, we leverage the newly collected *plant-level* information on the use and adoption of robots in the 2019 wave of the IAB Establishment Panel Survey to portray the state, the recent development, and the correlates of robot use and adoption in Germany, a country especially known for robot production and adoption.[2] Five stylized facts emerge. First, robot use is relatively rare, as only 1.55% of German plants used robots in 2018. Even in the manufacturing sector, only 8.22% of the plants were robot users. The finding is striking because Germany is the largest robot market in Europe and among the countries with the highest robot intensity in the world.[3] Second, the distribution of robots is highly skewed. Top 5% of the robot-using plants, in terms

[1] This chapter is joint work with Liuchun Deng and Jens Stegmaier and is published in the Journal of Economics and Statistics (November, 2023) with the same title.

[2] It should be noted that the development of robot-related questions in the survey and the data was a joint initiative of Steffen Müller from IWH and the three authors of this paper.

[3] See IFR's Annual Report, *World Robotics: Industrial Robots 2018*.

of robot stock, owned more than half of the total robot stock in 2018. Third, the new robot adopters, which represent the growth in the extensive margin, contributed substantially to the growth in the aggregate stock of robots (the intensive margin) from 2014 to 2018. Fourth, robot users are exceptional. Robot users in 2018 are found to be larger, have higher labor productivity, invest more, and be more likely to export and adopt up-to-date technology than non-robot-using plants. Last, plants use different types of robots and heterogeneity in robot types matters for an array of plant-level characteristics.

We further examine how robot adoption is *correlated* with ex ante plant-level characteristics.[4] Our regression results demonstrate plant size to be the most robust predictor of future robot adoption. Conditional on plant size, the share of high-skilled labor is negatively correlated and the exporter status is positively correlated with subsequent robot adoption. We also note different labor shortage measures to be differentially associated with robot adoption. Moreover, exploiting the introduction of minimum wage in 2015 in Germany, we obtain suggestive evidence that manufacturing plants that raise wages due to the minimum wage regulation are associated with a higher likelihood of robot adoption.[5] It is worth noting that we have established in one of the stylized facts that robot users are different from non-users. This fact is based on the cross-sectional regressions that relate plant-level characteristics with the contemporaneous status of whether a plant uses robots. Our main analysis is then to further explore what plant-level characteristics in 2014 are predictive of robot adoption in the *subsequent* period of 2015–2018. The exercise is correlational in nature and intended to shed light on the potential causes rather than consequences of robot adoption.

[4] All the results reported in this paper are correlational findings. We also try to avoid using causal phrases in interpreting our point estimates.

[5] The uniform minimum wage was introduced country-wide on January 1, 2015 and the hourly minimum wage was initially set at 8.50 Euros. For details on the minimum wage introduction and its employment effects, see Bossler and Gerner (2020) and Caliendo et al. (2019).

This paper joins a growing strand of work that collects and assembles firm- or plant-level data on robot use. Coming the closest is Koch et al. (2021) which is among the first to study robot adoption and its effects at the firm level based on a Spanish survey. Also using the Spanish data, Alguacil et al. (2022) provide robust evidence of a positive effect of robot adoption on export performance.[6] The survey dataset in both papers, unlike ours, does not contain direct intensive margin information on robot stock at the firm level. Dinlersoz and Wolf (2018) analyze the US Census Bureau's Survey of Manufacturing Technology which covers a variety of automation technologies including robots. Since large-scale robot-related surveys are still rare, an alternative data collection strategy is to infer robot use through international trade data. Humlum (2019) obtains Danish firm-level robot adoption data from the customs records and supplements that with a firm survey on the extensive margin information of robot use. Both Bonfiglioli et al. (2019) and Acemoglu et al. (2020) study robotization in France. The former examines robot importers and the latter identifies robot users by the French import data supplemented with robot sales information. To study the nexus between robots and organizational capital, Rodrigo (2022) also infer robot information at the municipality level from the Brazilian customs data.[7] We focus on Germany. Because of Germany's high robot density and its leading role in robot production, our analysis thus provides a microscopic portrait of a country on the frontier of robotization. The descriptive results can be informative for policymakers in Germany as well as in countries where robotization raises increasingly eminent policy discussions.[8]

Our findings on the correlates of robot adoption add to a vast literature on the diffusion of new technologies. Based on a 2018 large-scale data collection effort, Zolas

[6] For further work using the Spanish firm-level data, see Ballestar et al. (2020) and Stapleton and Webb (2020).

[7] Also see Cheng et al. (2019) for a survey of Chinese firms with robot-related questions, Barth et al. (2020) and Dixon et al. (2021) for trade-based measures in Norway and Canada, and a rapidly growing literature that goes substantially beyond industrial robots to broader automation measures based on the data in the Netherlands (Bessen et al., 2019), France (Aghion et al., 2020; Domini et al., 2021), and Finland (Hirvonen et al., 2022).

[8] After the working paper version of this paper was published (Deng et al., 2020), there is a growing interest in the German plant-level robot data. Most notably, Benmelech and Zator (2021) use the same data to examine robot adoption in relation to firm-level investment. We will discuss how some of our findings are related to theirs when we present the plant-level correlates of robot adoption in Section 3.

et al. (2020) describe the current state of advanced technologies adoption and use by the US firms. Bloom et al. (2021) adopt a big-data approach to study the diffusion of what they identify as disruptive technologies, including several automation technologies like autonomous cars and machine learning, across firms and regions in the US. As a first attempt to empirically assess firms' automation decisions in Germany, Zator (2019) exploits the broader measures of automation, including robots and CNC machines, and digitalization in the earlier waves of the IAB Establishment Panel Survey and highlights the role of labor scarcity in technology adoption. An emerging body of work in this literature focuses more specifically on the determinants of robot adoption. Similar to our findings, Koch et al. (2021) document positive effects of plant size, low-skilled labor intensity, and exporter status on subsequent probability of robot adoption. Using the firm-level data from China, Fan et al. (2021) find that higher labor costs, brought about by minimum wage legislation, incentivize firms to adopt robots.

Our work complements the existing studies based on the IFR data that exploit regional or cross-country industry-level variation in robot use. The seminal work by Graetz and Michaels (2018) documents a strong impact of robot use on labor productivity growth. de Vries et al. (2020) provide cross-country evidence of the rise of robots being associated with a decline in routine manual task intensive jobs. Based on a shift-share design, Acemoglu and Restrepo (2020) and Dauth et al. (2021) provide detailed analysis of how robots impact local labor markets in the US and Germany, respectively.[9]

Our paper does not examine the effects of robot adoption, but the stylized facts we document provide a useful context for the readers to interpret the existing findings that are based on more aggregate data. Among the few studies that study the causal determinants of robot adoption using (mainly) cross-country data, Acemoglu and Restrepo (2022) demonstrate demographic change to be an important driver of robot

[9] For further evidence on the labor market effects of robots in Europe, see Chiacchio et al. (2018) and Klenert et al. (2023). Borjas and Freeman (2019) compare the robot shock and the immigrant shock in the context of the US labor market. Stiebale et al. (2020) document the contribution of robots to the rise of superstar firms in Europe. For studies on the open-economy implications of robotization, see Artuc et al. (2020), Faber (2020), Furusawa et al. (2022), and Krenz et al. (2021).

adoption. Our findings also add to this strand of work by linking the underlying plant-level characteristics with robot adoption.

The rest of the paper is organized as follows. In the next section, we introduce the dataset and present the five stylized facts on robot use and adoption. In Section 3, we present the empirical results on the potential determinants of robot adoption. We provide concluding remarks in Section 4.

1.2 The Data and Stylized Facts

1.2.1 The Plant-level Data

The basis of our empirical analysis is drawn from the IAB Establishment Panel, an annual survey of nearly 16,000 plants, sampled from around 2 million German employers with a particular focus on employment.[10] The IAB Establishment Panel is a high-quality, long-standing panel data set that is nationally representative as a whole but also at the sector level, for firm-size classes, and across German federal states. In the 2019 wave, we included a dedicated section on robot use. Our definition of robots follows the ISO definition: A robot is any automated machine with multiple axes or directions of movement, programmed to perform specific tasks (partially) without human intervention. The difference between robots and traditional CNC machines is explicitly stated in the survey. The survey questions include (1) whether a plant used robots from 2014 to 2018; if so, (2a) the number of robots used in each year from 2014 to 2018 and (2b) the number of robots newly purchased in 2018; (3) heterogeneity regarding the types of robots in use.[11] The resulting plant-level data on robots is of high quality[12] and the distribution across industries is highly correlated with the industry-level IFR data for Germany (Plümpe and Stegmaier, 2022).

[10] We use the IAB Establishment Panel, Waves 2013 -2019. DOI: 10.5164/IAB.IABBP9319.de.en.v1. For more information on the IAB Establishment Panel, see Bechmann et al. (2019).

[11] An English translation of the survey questions can be found in the Appendix.

[12] For more details on data quality, consistency checks, and data cleaning, see Plümpe and Stegmaier (2022).

Table 1.1: Summary Statistics

	Year 2018			Year 2014		
Variable	Mean	Std. Dev.	N	Mean	Std. Dev.	N
log(Employment)	2.93	1.68	15,307	3.02	1.60	7,852
log(Labor Productivity)	10.63	0.84	8,267	10.57	0.86	4,945
log(TFP)	4.65	1.25	4,341	4.49	1.32	4,323
log(Wage)	7.38	0.68	8,563	7.38	0.66	5,542
High-Skilled Labor	0.09	0.19	11,470	0.09	0.19	6,942
Exporter	0.22	0.41	12,912	0.23	0.42	6,533

Notes: (1) The summary statistics are based on the sample of plants that provided a non-missing answer to whether they used robots in 2018. (2) No survey weights are applied. (3) Employment is the total employment count. Labor Productivity is defined as value added per worker in €1,000/Worker. TFP (total factor productivity) is the residual obtained by regressing the business volume on labor, capital, and intermediate input by industry. Capital stock is approximated using the method as in Müller (2017). Wage is the average monthly wage of all employees that are subject to social insurance contributions, including part-time employees and apprentices, calcuated as the total wage bill divided by the number of employees. High-skilled Labor is the share of workers with a university degree. Exporter is a dummy variable for exporter status.

Our dataset is the first longitudinal dataset that reports *direct* measure of robot use and intensity at the plant level. Due to the scarcity of microeconomic information on robotization, most of the existing papers infer the firm- or plant-level robot information indirectly from the import data (Acemoglu et al., 2020; Barth et al., 2020; Bonfiglioli et al., 2019; Humlum, 2019).[13] This approach not only suffers from the measurement error in trade classifications and domestic resales of robots as noted in the literature but also is much less feasible in the German context given the country's prominent role in robot production. Coming closest to our direct survey-based robot measures is the Spanish data used in Koch et al. (2021), whereas we also obtain direct robot information on the intensive margin.

Given the panel structure, we incorporate a wide array of plant-level variables since the 2013 wave of the IAB Establishment Panel. The resulting dataset is an unbalanced panel of 15,307 plants spanning from 2014 to 2018. Within our survey sample, 616 plants report using robots during the sample period. Table 1.1 reports the summary statistics for the main non-robot variables in 2014 and 2018. The sample size is larger

13 Acemoglu et al. (2020) supplement the French customs data with three additional data sources to help them identify the actual users of robots. Humlum (2019) also leverages a binary question on robot use in a 2018 Danish firm-level survey.

in 2018 because of the survey attrition when constructing our sample retrospectively based on the 2019 surveyed plants.

1.2.2 Stylized Facts

Based on the newly collected plant-level information on robots, we present five stylized facts concerning the use and adoption of robots in Germany. As the IAB Establishment Panel is based on a disproportionately stratified sample design, survey weights are applied to obtain representative results for Germany.[14] In what follows, we define a plant to be a *robot user* in a given year if that plant is identified to have a positive number of robots in that year and a plant to be a *robot adopter* over a given period if that plant is identified to have no robots at the beginning of that period and become a robot user by the end of the period.

Fact I: Robot use is relatively rare. In 2018, only 1.55% of the plants were robot users in Germany. Even within the manufacturing sector, the share of robot users is surprisingly small. According to Table 1.2, the manufacturing sector, which has undergone a continued process of robotization for more than five decades, has 8.22% of the plants being robot users in 2018.[15] The top two industries ranked by the share of robot users are plastics and motor vehicles. 25.55% of the plants in the plastics industry and 24.26% of the plants in the motor vehicles industry use robots, so the remaining three-quarters of the plants in these two most robot-intensive industries have not installed a single robot. In the precision/optical industry or other manufacturing industries like textiles and clothing, the share of robot users is below 5%, suggesting that robot use is rather an exception than norm even within the manufacturing sector.

[14] We focus on the results with survey weights in the main text and relegate some of the unweighted results to the Appendix.

[15] In Table 1.2, Column "Weighted" reports the share of robot users with survey weights and thus provides a representative picture of plant-level robotization for the entire country. Column "Unweighted" reports the unweighted share of robot users in each industry based on the survey sample. Since larger plants are over-sampled and, as will be discussed later, larger plants are more likely to be robot users, the unweighted share is generally larger than the weighted share. 4% of the surveyed plants, as opposed to 1.55% for the whole nation, reported robot use in 2018. But even based on the unweighted numbers, it remains evident that a relatively small share of plants use robots.

In the non-manufacturing sector, where robotic technology was brought into applications not long ago, 0.94% of the plants were robot users in 2018. Many non-manufacturing industries, especially service industries, have less than 1% of their plants being robot users.

Table 1.2: The Extensive Margin: Share of Robot Users by Industry in 2018

Industry/Sector	Weighted (%)	Unweighted (%)	# of plants
All Manufacturing	**8.22**	**14.52**	**3,257**
plastics	25.55	30.98	184
motor vehicles	24.26	30.50	200
basic metals	12.67	21.00	200
electrical equipment	11.33	15.34	163
machinery and equipment	11.29	15.90	434
furniture/jewelry/sports/medical	9.67	8.68	265
glass/ceramic	7.74	14.44	187
paper/print/wood	7.61	10.96	228
chemical/pharmaceutical	7.12	5.85	205
fabricated metal	6.22	17.07	457
food/luxury	5.87	10.54	313
precision/optical equipment	4.16	11.18	152
other manufacturing	1.27	1.49	269
All Non-manufacturing	**0.94**	**1.16**	**12,050**
agriculture/forestry	7.41	4.79	334
wholesale trade and retail trade	1.48	2.06	1649
building/installation	1.23	1.18	1103
human health	0.34	1.04	1828
other non-manufacturing	0.50	0.81	7136
Total	**1.55**	**4.00**	**15,307**

Notes: (1) Column *weighted* reports the share of robot users with survey weights. (2) Column *unweighted* reports the share of robot users without survey weights. (3) The last column reports the total number of surveyed plants (robot users and non-users combined). (4) The industries are based on the 2-digit IAB Establishment Panel Survey classification (aggregated from 2-digit NACE Rev.2 industries). (5) Due to very few observations of robot users, the following industries are combined into the *o*ther manufacturing category: textiles/clothing, repair/installation, and chemical/pharmaceutical. The residual category *other non-manufacturing* combines the sectors energy, sales/maintenance/repair of motor vehicles, financial/insurance sector, consulting, research/development, marketing/design/translation, veterinary industry, renting, placement/temporary provision of labor, itinerant trading/landscaping, activities of membership, and other services.

It should be noted that despite a relatively small share of plants using robots, those robot users employ a nontrivial fraction of the German workforce. Within the manufacturing sector, about 30% of the employees work for robot-using plants. Further, the share of robot users based on our sample is very similar to the 3% share of German enterprises using industrial robots based on the Eurostat ICT Community Survey in 2018 (Sostero, 2020).

Our findings can also be usefully compared with the numbers based on the US data. In the 2018 Annual Business Survey (ABS) that covered more than 850,000 US firms in the nonfarm sectors, Zolas et al. (2020) document that 1.3% of the firms use robotics, which is slightly lower than the robot-user share of 1.55% (adjusted for survey weights) in Germany. In the US Census Bureau's Survey of Manufacturing Technology (SMT) which was conducted in 1988, 1991, and 1993, Dinlersoz and Wolf (2018) document a larger share of plants used robots for five manufacturing industries.[16] For example, they find that 7.7% of the plants in 1988 used pick and place robots. The industry-level user share in Germany as in Table 1.2 suggests a similar pattern: the more capital-intensive manufacturing industries tend to use robots more extensively.

Fact II: The robot distribution is highly skewed. Among the robot users, robots are highly concentrated in a handful of heavy users and high concentration is mainly driven by the skewed distribution of robots in the manufacturing sector. In 2018, 52% of the total robot stock is estimated, based on the survey weights, to be installed in top 5% of the robot using plants (ranked by the plant-level robot count) in Germany, whereas within the survey sample, 85% of the total robot stock is installed in top 5% of the robot using plants. According to the first panel of Figure 1.1, manufacturing plants in the top decile on average have 40 robots, 20 times as many as the median number of robots among robot users. Within the top decile, the distribution of robots is also highly skewed: the highest two percentiles have on average 141 robots.[17]

[16] SMT was designed to focus on industries that are more likely adopt automation technologies. The five industries are fabricated metal, machinery, transportation equipment, electronics, and instrument.

[17] Without survey weights the robot distribution is even more skewed, as shown in Figure A1.1 in the Appendix.

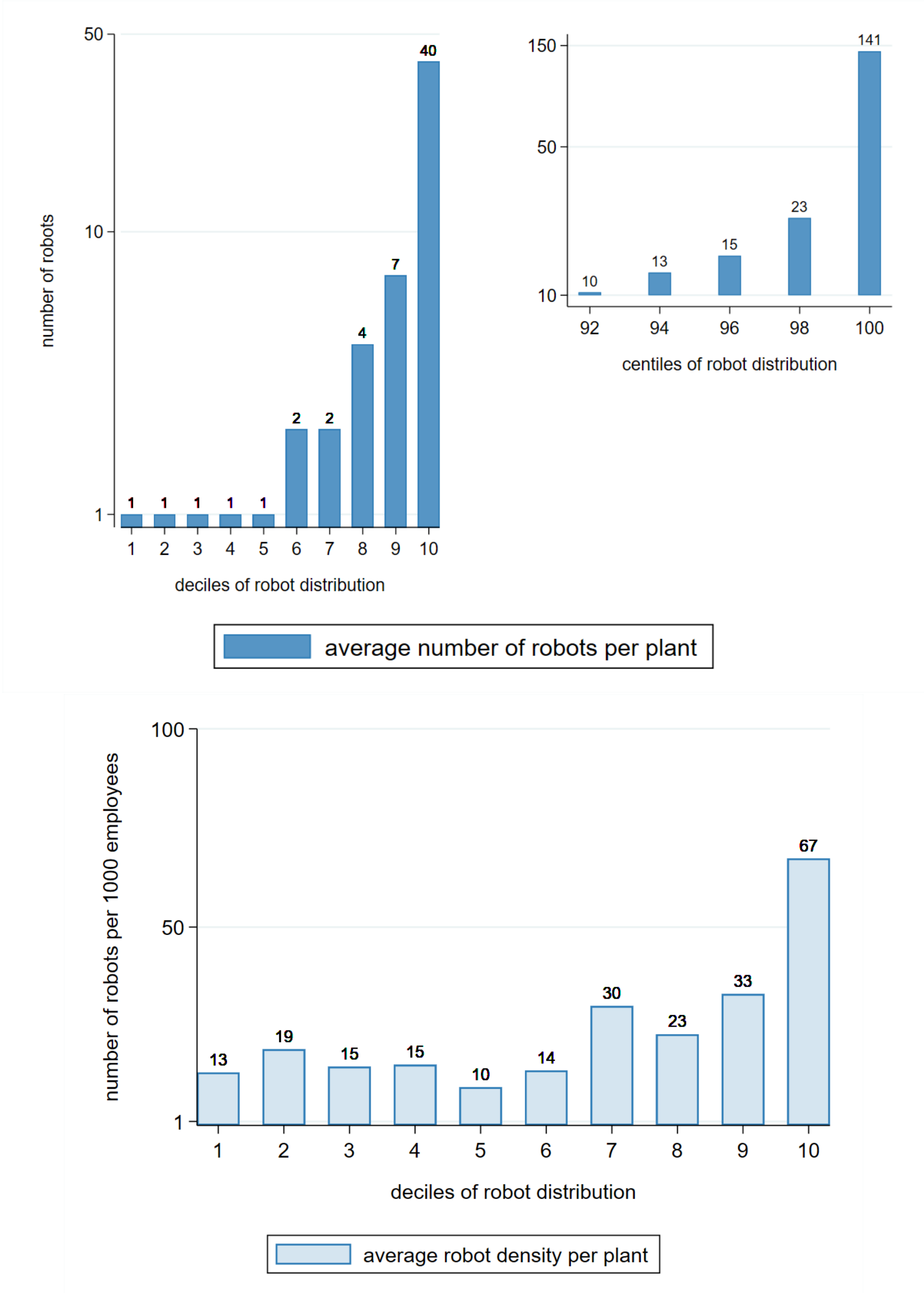

Figure 1.1: The Intensive Margin: Distribution of Robots in Manufacturing in 2018

Notes: (1) We sort plants by the number of robots reported in 2018. For plants with the same number of robots, they are randomly sorted (a further sorting by plant-level attributes like plant size could artificially skew the distribution of robot intensity). The same sorting is applied to both panels. (2) Survey weights are applied. (3) Average robot count or robot density (measured by robot count per 1,000 employees) is calculated within each decile or bi-centile and rounded to the closest integer. (4) Due to skewedness of the distribution, the first panel is plotted in log scale.

Based on the same sorting of plants, the second panel of Figure 1.1 further demonstrates that the high concentration of robots is not just reminiscent of the skewed distribution of plant size. The average robot density, measured by the number of robots per 1,000 employees, is substantially higher for the top decile, so the distribution of robots is more skewed than the employment distribution across plants.

It is worth noting that high concentration of robots in the manufacturing sector is not just driven by the large automobile plants. Indeed, the plants with the highest number of robots are mainly in the motor vehicle industry, but the robot distribution for the non-automobile manufacturing plants remains very skewed. An inspection of the within-industry robot distribution suggests that robots are highly concentrated in almost all manufacturing industries.[18] In contrast, the distribution of robots is much less skewed in the non-manufacturing sector. Using the survey weights, we estimate about a quarter of the robots to be installed in the non-manufacturing sector. The median user installed one robot in 2018 while the users in the top decile had 7 robots on average. The lack of skewedness is largely a reflection of the early stage of robotization in the non-manufacturing sector. It is worth tracking if the different nature of robotic technology (for example, service robots) used in non-manufacturing may also impact the concentration of robots in this sector in the long run.

Fact III: The extensive margin contributes substantially to robotization. Robot adopters, the plants that newly adopted robots from 2014 to 2018, make a substantial contribution to the growth in both the share of robot users and the total robot stock. In our survey sample, 189 plants, around 30% of all the robot users in 2018, report that they newly adopted robots during the period from 2014 to 2018. Figure 1.2 compares across industries the share of robot users in 2014 with that in 2018.[19] The share of robot users in the manufacturing sector increases by more than 50% from

[18] Based on the 2018 ABS data, Zolas et al. (2020) also note that the distribution of robots is highly skewed in the US and concentrated in large manufacturing firms.

[19] We use the 2018 survey weights to calculate the user shares in 2014 and 2018 in Figure 1.2. Ideally, we should use the 2014 survey sample and the corresponding weights to calculate the user share in 2014. However, as the robot data was only collected in 2019 through retrospective questions, we do not have fully representative data for earlier years. Without survey weights the pattern remains qualitatively the same, as depicted in Figure A1.2 in the Appendix.

5.16% to 8.22%.[20] The user share in the non-manufacturing sector almost doubles from 0.51% to 0.94%. In the motor vehicle industry, one of the most robot-intensive industries, the user share increases from 16.90% to 24.26%.[21]

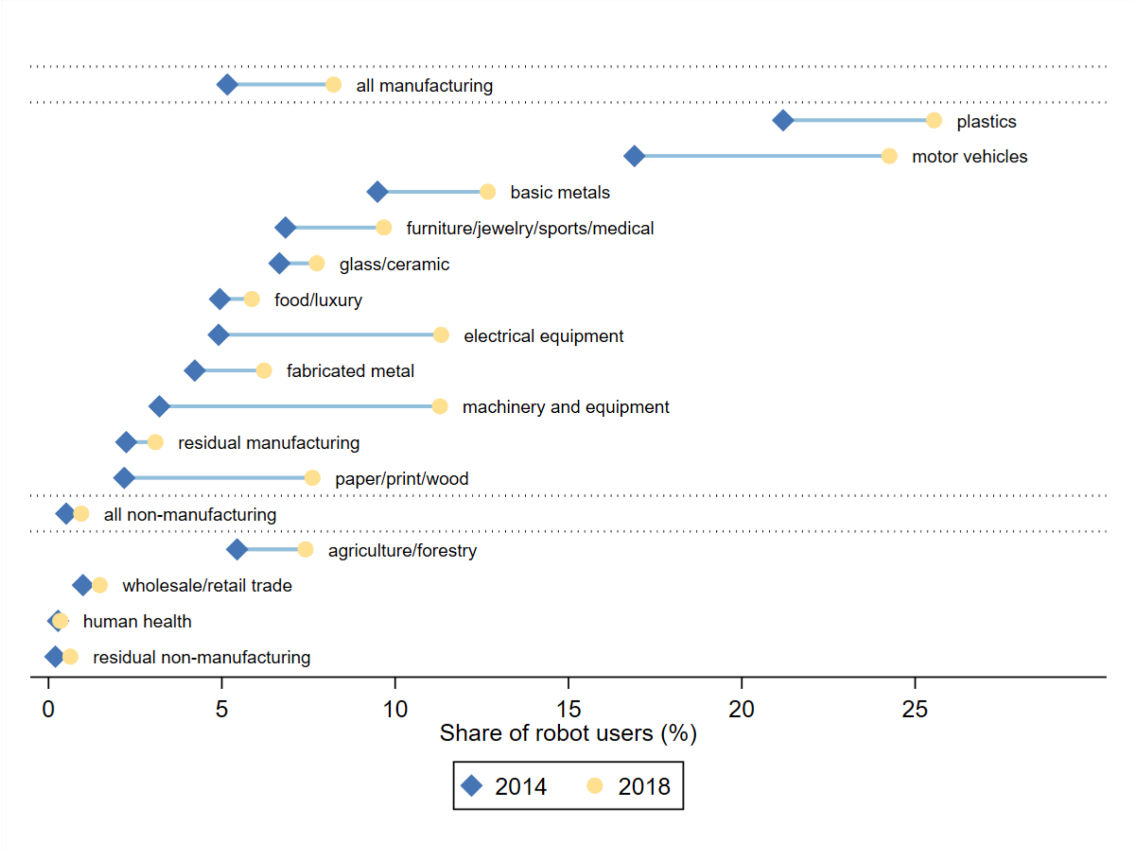

Figure 1.2: Share of Robot Users: 2014 versus 2018

Notes: (1) A plant is identified as a robot user in 2018 if it answered yes to the question of whether it used robots from 2014 to 2018 and its robot stock in 2018 was not zero. (2) Survey weights in 2018 are applied. (3) The estimated share of robot users in 2014 is the share of robot users in 2018 times the share of plants reporting a positive robot stock in 2014 within the sample of robot users in 2018 reporting a non-missing robot stock in 2014. (4) The industries included in the figure are based on the 2-digit IAB Establishment Panel Survey classification (aggregated from 2-digit NACE Rev.2 industries). Due to very few observations of robot users, the following industries are combined into a residual manufacturing category: textiles/clothing, repair/installation, precision/optical equipment, and chemical/pharmaceutical.

[20] Zolas et al. (2020) document that 0.3% of the US firms were testing robots in 2017, compared with the user share of 1.3% in the same year. This is suggestive that the potential increase in the extensive margin can also be sizable in the US.

[21] It should be noted that out of the 616 plants that report using robots from 2014 to 2018 in our survey sample, 104 (≈ 17%) plants do not provide information on their robot stock in 2014. Due to the missing values for the robot stock in 2014, the share of robot users in 2014 is estimated based on the plants that report consistently their robot stocks throughout the sample period. Figure A1.3 in the Appendix presents both the lower and upper bounds for the estimated share of robot users in 2014. The lower bound is calculated by assuming that all the plants with missing robot stock in 2014 were not robot users and the upper bound is calculated by assuming that those plants were all robot users in 2014. It is reassuring that even the most conservative estimate, based on the upper bound of the user share in 2014, suggests that the user share rose considerably by more than a third from 2014 to 2018 in the manufacturing sector.

Moreover, divestment in robots is rarely observed in our sample. Only two plants that once used robots report decreasing their robot stock to zero by the end of the sample period.

To bring out the role of the intensive margin, Figure 1.3 plots the growth of robot stock by industry from 2014 to 2018.[22] The industry-level growth is decomposed into the extensive and intensive margins. The extensive margin, illustrated by the light-colored bars, is the contribution of robot adopters from 2014 to 2018 to the overall growth of robots, whereas the intensive margin, illustrated by the dark-colored bars, is the contribution of the plants that already used robots in 2014. In the manufacturing sector, the overall growth in robot stock is 44% and 13 percentage points are contributed by new adopters; In the non-manufacturing sector, robot stock in total increases by 132% and 114 percentage points are contributed by new adopters.

Two notable features are worth highlighting. First, the aggregate numbers for the manufacturing sector mask substantial heterogeneity across industries. For example, in the electrical equipment industry, the new adopters play a dominant role in robot growth, raising the industry-level robot stock by about 260% (out of the overall growth rate of 312%). Similarly, in paper, print, and wooden products industry, robot stock grows by 214%, among which 157 percentage points are contributed by new adopters. The growth pattern in those industries stands in sharp contrast to the motor vehicle industry where robots have been traditionally heavily used and the overall growth in robot stock is mainly contributed by the existing users. Second, the contribution of the extensive margin to growth is much greater in the non-manufacturing sector. The new robot purchases are predominantly made by robot adopters, consistent with rapid growth in the robot user share of the non-manufacturing sector as shown in Figure 1.2.[23]

[22] For the decomposition without survey weights, see Figure A1.4 in the Appendix.

[23] Hidden in Figure 1.3 is the number of robots being replaced. According to the survey answers, a significant share of the new robot installations in 2018 can be attributed to replacement of the existing robots, echoing a channel formally modeled in Humlum (2019) and also extensively discussed in the earlier literature on vintage capital models (Benhabib and Rustichini, 1991; Boucekkine et al., 1997).

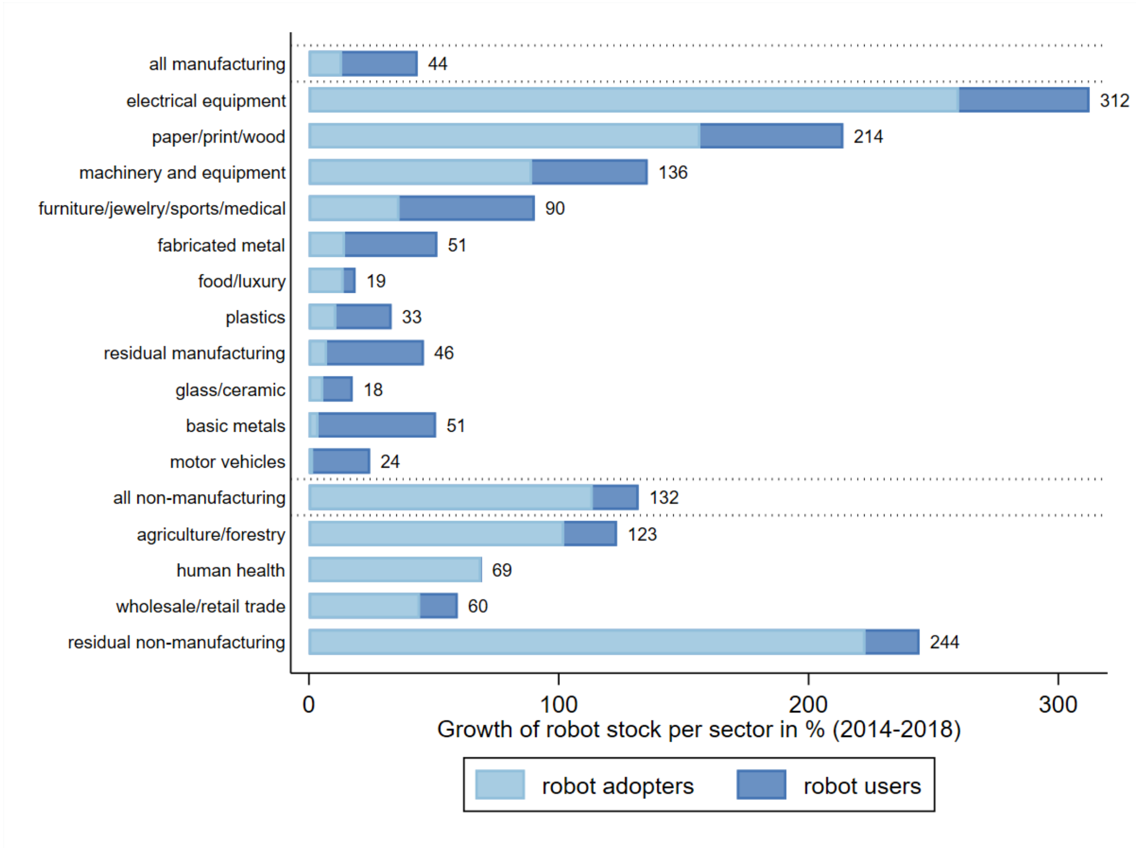

Figure 1.3: Decomposition of Growth in Robot Stock: The Extensive versus Intensive Margin

Notes: (1) Calculations are based on the surveyed plants that reported their robot use in each year from 2014 to 2018. Survey weights in 2018 are applied. (2) For each industry (sector), the contribution of the robot adopters to growth is defined as the ratio of the total robot stock of robot adopters in 2018 to the robot stock aggregated over the existing users in 2014. The contribution of the existing robot users to growth is defined as the percentage change of the aggregate robot stock from 2014 to 2018 for the plants that already used robots in 2014. (3) The industries included in the figure are based on the 2-digit IAB Establishment Panel Survey classification (aggregated from 2-digit NACE Rev.2 industries). Due to very few observations of robot users, the following industries are combined into a residual manufacturing category: textiles/clothing, repair/installation, precision/optical equipment, and chemical/pharmaceutical.

Our findings, taken together, point to the importance of the extensive margin. It indicates that the recent wave of robotization is not only a process of capital deepening for the existing users but also a classic example of technology diffusion, as more and more plants reap the benefits of the new automation technology.

Fact IV: Robot users are exceptional. Robot users are different. In 2018, only 1.55% of the German plants used robots, but they employed 3.2 million workers, which account for about 8% of the total labor force in Germany. To capture robotization premia,[24] that is, how robot users differ from non-users in a wide array of plant-level

[24] This term, "robotization premia", is meant to draw a direct parallelism with the exporter premia as in Bernard et al. (2007, 2018).

characteristics, we use the 2018 cross-sectional sample to perform the following bivariate regressions:

$$X_{ijk} = \alpha + \beta \text{RobotUse}_{ijk} + \phi_j + \psi_k + \gamma \log(\text{Emp}_{ijk}) + \varepsilon_{ijk}, \tag{1.1}$$

where X_{ijk} is a given characteristic of interest for plant i in industry j and state k; RobotUse_{ijk} is a dummy variable which equals one if plant i used robots in 2018 and zero otherwise; ϕ_j and ψ_k are the industry and state fixed effects; Emp_{ijk} is the plant-level employment count. Our specification takes into account important features that approximate the sample design of the IAB Establishment Panel (plant size, state, and industry), so we do not weight our regressions and present regression results without survey weights throughout this paper for conciseness.[25] We have also run the same regression specification with survey weights, but the implications based on these results are qualitatively the same. Thus, our regression results can be viewed as representative for Germany.

Table 1.3 presents the estimates of β for a number of plant-level characteristics for five different specifications. In the first row, all the bivariate regressions are based on the full sample without any fixed effects or a plant size control. We then include industry and state fixed effects in the second row and additionally employment as a plant size control in the third row. In the last two rows, we run the bivariate regressions with the fixed effects and the employment control for the manufacturing and non-manufacturing sample separately. Since employment is used as an additional control, the point estimates for employment drop out in Columns (1) and (2) for the last three specifications. It should be noted that the sample size varies across different columns in Table 1.3 because the fraction of missing values varies with the plant-level characteristics.[26]

[25] For a detailed comparison between weighted regressions and unweighted regressions with the elements of the survey design being controlled for, see Bossler et al. (2018).

[26] To ensure that our results are not driven by sample selection, we rerun all the specifications in Tables 1.3–1.5 based on a restricted sample that only consists of plants with non-missing information about labor productivity, wage, exporter and technology status, innovation activities, and investment. The results are qualitatively similar and available upon request.

Table 1.3: Robotization Premia: The Extensive Margin

	Dependent Variable									
	Employment	Labor Productivity	TFP	High-Skilled Labor	Wage	Exporter	Up-to-date Technology	Product Improvement	Process Improvement	Investment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No Control	1.783***	0.551***	-0.082	0.003	0.408***	0.462***	0.032	0.347***	0.305***	2.289***
Full Sample	(0.162)	(0.062)	(0.134)	(0.013)	(0.061)	(0.037)	(0.030)	(0.024)	(0.025)	(0.218)
FE	1.418***	0.306***	0.093*	0.020***	0.216***	0.228***	0.117***	0.237***	0.250***	1.657***
Full Sample	(0.122)	(0.043)	(0.049)	(0.007)	(0.040)	(0.026)	(0.025)	(0.020)	(0.022)	(0.158)
FE + Size		0.123***	0.087*	-0.009	-0.018	0.168***	0.086***	0.152***	0.191***	0.600***
Full Sample		(0.042)	(0.053)	(0.008)	(0.036)	(0.025)	(0.026)	(0.020)	(0.022)	(0.097)
FE + Size		0.055	0.041	-0.019***	-0.043	0.072***	0.060*	0.091***	0.140***	0.383***
Manuf.		(0.042)	(0.035)	(0.006)	(0.026)	(0.026)	(0.032)	(0.023)	(0.028)	(0.094)
FE + Size		0.095	0.237*	0.018	-0.079	0.090**	0.139***	0.173***	0.215***	0.706***
Non-manuf.		(0.083)	(0.142)	(0.018)	(0.105)	(0.040)	(0.042)	(0.039)	(0.048)	(0.196)

Notes: (1) The table reports OLS regression results of Equation (1.1). Each column reports for five different specifications, the estimated coefficient of the dummy variable of robot use by regressing a given plant-level characteristic on the robot-use dummy (and additional controls). (2) No survey weights are applied. (3) The dependent variables, Employment, Labor Productivity, TFP, Wage, and Investment, are all in log values. Exporter, Update-to-date Technology, Product Improvement, and Process Improvement are dummy variables. High-skilled Labor is the share of employees with a university degree. (4) Each row represents a different regression specification. The first three specifications are based on the full sample (N=14,263). The fourth specification is based on the manufacturing sample (N=3,068) and the fifth is based on the non-manufacturing sample (N=11,195). The actual sample size varies across plant-level characteristics due to the missing values. For the full sample estimation, the sample size is 14,263 for (1), 7,671 for (2), 4,046 for (3), 10,440 for (4), 7,807 for (5), 11,982 for (6), 10,142 for (7), 14,174 for (8), 14,177 for (9), and 8,167 for (10). In the first specification ("No Control"), there is no additional control. The second specification ("FE") includes industry (2-digit NACE Rev.2 industries) and federal state fixed effects. The last three specifications ("FE + Size") include both fixed effects and plant-level employment (in log) as controls. (5) Standard errors are clustered at 3-digit NACE Rev.2 level and reported in parentheses. (6) *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Overall, the estimated coefficients suggest that robot users are about four times ($e^{1.418} \approx 4.129$) as large as non-users (Column (1)). Without controlling for the plant size, our point estimates in the second row suggest that robot users are different from non-users along all dimensions of plant-level characteristics. However, once we control for the plant size as in the third row, the differences between the users and non-users in skill intensity and wage (Columns (4)–(5)) are no longer statistically significant. Columns (2) and (3) suggest that even after controlling for the plant size, robot users are more productive than non-users.

Columns (6)–(9) report the point estimates for four dummy variables, capturing the exporter and technological status as well as product and process improvement. According to Column (6), the probability of being an exporter is 16.8 percentage points higher for robot users. According to Column (7), the probability of adopting up-to-date or relatively up-to-date technology increases by 8.6 percentage points for robot users.[27] This correlation between robot use and technological status is consistent with the findings of the adoption of new technologies being interconnected in Zolas et al. (2020). Further, Columns (8) and (9) suggest a positive association between automation and innovation: robot users are more likely to engage in product and process improvement. In Column (10), we find that robot users also make significantly more investments.

We now turn to the last two rows in Table 1.3 which estimate robotization premia separately for the manufacturing and non-manufacturing plants. The main patterns for the two subsamples are largely similar to those for the full sample, with two notable exceptions. First, the estimated premium for labor productivity in Column (2) is no longer significant for both subsamples with reduced magnitude,[28] so there is a caveat in interpreting labor productivity premium based on the full sample result. Second, Column (4) reveals an interesting asymmetry concerning the skill intensity. In the

[27] In the original survey question, there are five technological statuses: (a) up-to-date; (b) relatively up-to-date; (c) relatively outdated; (d) outdated; (e) completely outdated. We define the dummy variable as being equal to one if a plant answers its technology being up-to-date or relatively up-to-date.

[28] It should also be noted that the subsample estimates for the exporter status in Column (6) are also substantially smaller than the full-sample point estimate. We thank one of our reviewers for raising this point.

manufacturing sector, the share of high-skilled labor (employees with a university degree), with the plant size being controlled for, is 1.9 percentage points lower for robot users, whereas in the non-manufacturing sector, robot users are as skill-intensive (measured by the high-skilled labor share) as non-users. We will revisit this asymmetry later as we explore the correlates of robot adoption.[29]

Fact V: Heterogeneity of robots matters. Technological progress in the last decade has been shaking the stereotype of (industrial) robots. Robots that can be used in collaboration with human workers, usually smaller in size and cheaper in price, are on the rise. To have a fuller picture of robotization, it is important to account for the composition of different types of robots at the plant level and how the compositional difference manifests itself in plant-level outcomes. The questions on heterogeneity in robots in our survey enable this inquiry.

According to our survey, 49% of the German robot-using plants report using robots that are separated from employees during regular operations with the help of a protection device (labeled as "cage robots" henceforth), which are distinguished from the new collaborative robots, and 54% of the robot using plants report using robots that cost more than 50,000 Euros (labeled as "expensive robots" henceforth) in 2018. Among those cage robot users, 85% of them have all of their robots operated in separation from employees, accounting for 72% of the total robot stock. Among those expensive robot users, 78% of them have all of their robots purchased at a price above 50,000 Euros, accounting for 45% of the total robot stock.[30]

Leveraging the information on robot types, we reexamine robotization premia on the extensive margin. We consider the regression of the following form:

$$\begin{aligned} X_{ijk} = \alpha &+ \beta_1 \text{RobotUse}_{ijk} + \beta_2 \text{RobotUse}_{ijk} \times \text{Cage}_{ijk} \\ &+ \beta_3 \text{RobotUse}_{ijk} \times \text{Expensive}_{ijk} + \phi_j + \psi_k + \gamma \log(\text{Emp}_{ijk}) + \varepsilon_{ijk}, \end{aligned} \tag{1.2}$$

[29] In the Appendix, we also report the robotization premia on the intensive margin within the sample of robot users.

[30] These shares are calculated with survey weights. Within the survey sample, close to 70% of the robot users use cage robots and 65% of them use expensive robots.

where RobotUse_{ijk} is the dummy of whether a plant is a robot user as we have defined before, Cage_{ijk} is a dummy variable that equals one if a robot user has its *all* robots being cage robots, and Expensive_{ijk} is a dummy variable that equals one if a robot user has its *all* robots being purchased at a price of above 50,000 Euros. Note that cage robot users and expensive robot users are not mutually exclusive. The control group in this specification is the non-robot-using plants.

Table 1.4 reports the estimation results. According to Column (1), robot users are significantly larger than non-users, but this size premium is particularly large for cage robot and expensive robot users. Compared with other robot users, cage robot users are on average about 46.7% larger ($e^{0.383} - 1 \approx 0.467$) and expensive robot users are about 55.3% larger ($e^{0.440} - 1 \approx 0.553$). Conditional on plant size being controlled, however, expensive robot users do not significantly differ from other robot users along other plant-level characteristics, whereas cage robot users tend to hire less high-skilled

Table 1.4: Robotization Premia: Heterogeneity in Robot Types

	Dependent Variable					
	Employment	Labor Productivity	TFP	High-Skilled Labor	Wage	Exporter
	(1)	(2)	(3)	(4)	(5)	(6)
RobotUse	0.766***	-0.025	0.117	0.015	0.009	0.081**
	(0.188)	(0.074)	(0.125)	(0.018)	(0.059)	(0.036)
RobotUse×Cage	0.383**	0.116	-0.094	-0.035**	-0.005	0.099**
	(0.163)	(0.075)	(0.103)	(0.016)	(0.050)	(0.044)
RobotUse×Expensive	0.440**	0.092	0.052	0.007	-0.034	0.031
	(0.193)	(0.060)	(0.085)	(0.013)	(0.049)	(0.036)
Plant Size	No	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	14,166	7,630	3,960	10,391	7,786	11,861
Adjusted R^2	0.271	0.282	0.798	0.281	0.423	0.309

Notes: (1) This table reports the OLS regression results for Equation (1.2). (2) No survey weights are applied. (3) In 2018, 391 plants solely used cage robots (RobotUse×Cage=1), 323 plants solely used expensive robots (RobotUse×Expensive=1), and 268 plants solely used both cage and expensive robots (RobotUse×Cage=RobotUse×Expensive=1). (4) The dependent variables, Employment, Labor Productivity, TFP, and Wage, are all in log values. Exporter is a dummy variable. High-Skilled Labor is the share of employees with a university degree. (5) All regressions are based on the full sample (both manufacturing and non-manufacturing plants included) and include both 2-digit NACE Rev.2 industry and federal state fixed effects and the employment count (in log) as controls. (6) Standard errors are clustered at 3-digit NACE Rev. 2 level and reported in parentheses. (7) *** p<0.01, ** p<0.05, * p<0.1.

labor (Column (4)) and enjoy a much higher premium in the probability to export (Column (6)).[31]

Those results taken together point to the importance of accounting for different types of robots: not all robots are the same. Since robotization premia are heterogeneous across robot types, it could be the case that the labor market consequences of robotization may also hinge on which type of robots is more complementary or substitutable to human labor. With the rapid development in robotics, our correlational observations thus call for a more systematic attempt in future survey designs to solicit more details on heterogeneity in robot types.

1.3 Plant-level Correlates of Robot Adoption

In this section, we explore the correlates of robot adoption. In Germany, robot users differ from non-users in a number of ways, as shown in Stylized Fact IV. To examine whether these differences precede the adoption of robots and what may constitute the potential determinants of adoption, we focus on the sample of plants that reported no robot use in 2014 to investigate which plant-level characteristics in the base year correlate with robot adoption in subsequent years.[32] Our baseline cross-sectional specification is given by

$$\text{RobotAdp}_{ijk}^{2015-2018} = \alpha + X_{ijk}^{2014}\beta + \phi_j + \psi_k + \varepsilon_{ijk}, \tag{1.3}$$

where X_{ijk}^{2014} is a set of plant-level characteristics in 2014 for plant i in industry j and state k; $\text{RobotAdp}_{ijk}^{2015-2018}$ is a dummy variable which equals one if a plant that did

[31] We again relegate the results on the intensive margin concerning the heterogeneity of robot types to the Appendix. Moreover, we rerun the specifications in Table 1.4 using the restricted sample as described in Footnote 26. The results are qualitatively similar with two slight differences: (i) for plant size (employment), plants using exclusively expensive robots are no longer significantly different from other robot users; (ii) for exporter status, RobotUse is no longer significant.

[32] We exclude from our regression sample the plants that already used robots in 2014 as they did not have a robot adoption decision to make. Theoretically, if we assume there is a fixed cost of robot adoption (due to the changes in production settings or management that robotic technologies can bring about), then the adoption decision for non-robot-using plants is very different from the existing robot users'.

not use robots in 2014 newly adopted robots from 2015 to 2018 and zero otherwise; ϕ_j and ψ_k are the industry and state fixed effects. Based on our definition of robot adoption, 189 plants in total are identified as robot adopters from 2015 to 2018, among which 33 adopted robots for the first time in 2015, 44 in 2016, 34 in 2017, and 78 in 2018.

The task-based theoretical framework of robot adoption with firm heterogeneity has identified a variety of microeconomic factors that can influence firms' automation decisions (Acemoglu and Restrepo, 2018; Koch et al., 2021). Assuming the fixed cost of robot adoption, Koch et al. (2021) demonstrates theoretically that larger firms or firms with access to international markets have more incentives to adopt robots because they are more likely recover the fixed adoption cost, whereas firms with higher skill intensity are less likely to adopt robots because tasks that required more skilled labor to perform are generally more difficult to automate. It is also shown that the labor cost matters as higher labor cost can imply larger cost savings by robot adoption. Our empirical analysis will focus on plant size and productivity, skill composition and labor cost measures, and internationalization measures as potential correlates of robot adoption. We will also consider direct survey responses to various labor market constraints that plants are faced with.

Table 1.5 presents the baseline regression results for the full sample. In all specifications, we include industry and state fixed effects. In Columns (1) and (2), we find future robot adoption to be positively associated with labor productivity and employment. Consistent with the theoretical prediction and earlier empirical findings, larger and more productive plants are more likely to adopt robots.[33] In Columns (3)–(8), we include employment as a plant size control. Plant size always enters the regression significantly with a positive sign.

[33] An alternative interpretation of the robust association of plant size with adoption is that plant size may proxy for many other forms of technology upgrading taking place at plants, and thus robot adoption should be viewed as part of a continued process of automation rather than a disruptive new technology (Fernandez-Macias et al., 2021).

Table 1.5: Correlates of Robot Adoption: Baseline Specification (Full Sample)

	Dependent Variable: Robot Adoption Dummy (= 1 if a plant newly adopted robots between 2014 and 2018)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Labor Productivity	0.005*									
	(0.003)									
Employment		0.008***	0.013***	0.009***	0.010***	0.008***	0.009***	0.011***	0.008***	0.009***
		(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
TFP			-0.002							
			(0.002)							
High-Skilled Labor				-0.012*						
				(0.006)						
Wage					-0.003					
					(0.003)					
Minimum Wage						0.004				
						(0.005)				
Exporter							0.028***			
							(0.006)			
Foreign Ownership								0.023		
								(0.015)		
Demand for Training									0.011**	
									(0.006)	
Skilled Labor Shortage										-0.006
										(0.004)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,242	6,822	3,803	5,978	4,776	6,610	5,616	4,731	5,849	5,849
Adjusted R^2	0.028	0.043	0.041	0.042	0.043	0.042	0.047	0.042	0.042	0.042

Notes: (1) The table reports the OLS regression results for Equation (1.3). (2) No survey weights are applied. (3) All the independent variables are measured as of year 2014, except for the minimum wage dummy which is taken from the 2015 survey. (4) The independent variables, Employment, Labor Productivity, TFP, and Wage, are all in log values. High-skilled Labor is the share of employees with a university degree. Minimum Wage is a dummy variable that equals one if the plant raised wages due to the minimum wage regulation in 2015. Exporter, Foreign Ownership, Demand for Training, and Skilled Labor Shortage are dummy variables for the exporter status, foreign ownership, whether a plant experienced staffing problems that demand for further training, and whether a plant reported skilled workers hard to find, respectively. (5) Both industry (2-digit NACE Rev.2) and federal state fixed effects are included. (6) Standard errors are clustered at the 3-digit NACE Rev.2 level and reported in parentheses. (7) *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

With the plant size being controlled for, we do not find evidence of TFP to be associated with subsequent robot adoption in Column (3). In Column (4), we find the share of high-skilled labor (employees with a university degree) in the initial year lowers the probability of robot adoption. This again is consistent with the skill composition channel identified in theory: other things equal, high-skilled labor which has comparative advantage in performing more complex and less automatable tasks is less likely to be replaced by robots. According to Column (5), the average wage, arguably a crude measure of plant-level skill intensity, however, shows no significant association with robot adoption.

In Column (6), we consider the effect of the introduction of minimum wage in 2015 in Germany. We define the minimum wage dummy as one if a plant answered in the 2015 survey that it raised its wages due to the new minimum wage regulation. The dummy variable enters the regression positively but with no statistical significance. In Columns (7) and (8), we examine the two internationalization measures, exporter status and foreign ownership, with the former being strongly and positively correlated with adoption, similar to the findings in Koch et al. (2021).

In Columns (9) and (10), we introduce two labor shortage measures to capture whether plants have demand for further training of their employees and whether they have difficulties in finding skilled labor. The two measures enter the regressions with opposite signs. The demand for further training is associated with a higher probability of subsequent robot adoption, whereas the shortage of skilled labor, despite the lack of statistical significance, is associated with a lower adoption probability. The point estimates in Columns (9) and (10) suggest a nuanced picture of how labor shortage impacts robot adoption. In contrast to the findings in Benmelech and Zator (2021) that general labor shortage measures are associated with stronger automation incentives, we find that the lack of qualified skilled employees, which are likely complementary factors to robots, may potentially lower the probability for firms to adopt robots.

The correlational findings in Table 1.5, albeit intriguing, may be viewed as inconclusive given its parsimonious specification. Table 1.6 then presents the regression results for specifications in which we include simultaneously all the main correlates of robot adoption.[34]

In Column (1), plant size, high-skilled labor share, exporter status, and labor shortage measures are estimated significantly and consistent with the baseline results. In Column (2), our preferred specification for the full sample, we further control for a wide array of plant-level characteristics which may potentially impact robot adoption,[35] and the result remains robust. According to the point estimates, a one-standard-deviation difference in log(employment) in 2014, which is 1.6, is associated with a 1.28-percentage-point difference in the probability of robot adoption. A one-standard-deviation difference in the share of high-skilled labor in 2014, which is 0.19, is associated with a 0.57-percentage-point ($0.19 \times (-0.030) \approx -0.57\%$) difference in adoption probability, and being an exporter is associated with a higher adoption probability by 3.0 percentage points. Compared with the within-sample unconditional probability of robot adoption being around 2.5% over this period, the effects of plant size, skill composition, and exporter status on robot adoption are quite substantial in their magnitude.

Columns (3)–(6) in Table 1.6 further report the full-specification regression results separately for the manufacturing and non-manufacturing samples. The starkest difference between the manufacturing and non-manufacturing sample results lies in the high-skilled labor share. For the manufacturing sample, this skill composition measure is estimated highly significant with an increased magnitude, as in Columns (3) and (4). A larger share of college-educated employees predicts a much smaller probability of robot adoption in the future.

[34] We also estimate the full specifications using an outcome-based proxy for plant size, business volume, and all the main results are qualitatively the same.

[35] These additional controls are dummies for works council, technological status, process improvement, degree of competition, and foreign ownership.

In contrast, this effect is muted in the non-manufacturing sample. According to Columns (5) and (6), there is virtually no correlation between the share of high-skilled labor and adoption. Recall that we have documented earlier that robot users employ a significantly smaller share of high-skilled labor than non-robot-using plants in the manufacturing sector, but that is not the case for the non-manufacturing sector. In light of the findings here, this interesting asymmetry perhaps precedes robot adoption and reflects the differential selection mechanisms of plants into adoption in the two sectors.

Table 1.6: Correlates of Robot Adoption: Full Specification

	Dependent Variable: Robot Adoption Dummy					
	Full Sample		Manufacturing		Non-Manufacturing	
	(1)	(2)	(3)	(4)	(5)	(6)
Employment	0.010***	0.008***	0.032***	0.024***	0.003***	0.002
	(0.002)	(0.002)	(0.007)	(0.007)	(0.001)	(0.002)
High-Skilled Labor	-0.025*	-0.030*	-0.139***	-0.137***	0.003	0.003
	(0.013)	(0.016)	(0.043)	(0.044)	(0.011)	(0.015)
Minimum Wage	0.004	0.008	0.016	0.030*	-0.000	-0.002
	(0.005)	(0.006)	(0.016)	(0.016)	(0.004)	(0.004)
Exporter	0.032***	0.030***	0.037***	0.037***	0.014**	0.014**
	(0.007)	(0.006)	(0.013)	(0.012)	(0.006)	(0.006)
Demand for Training	0.016**	0.016*	0.038*	0.032	0.008	0.010
	(0.008)	(0.008)	(0.022)	(0.022)	(0.006)	(0.007)
Skilled Labor Shortage	-0.010**	-0.008	-0.009	-0.003	-0.009***	-0.008**
	(0.005)	(0.005)	(0.013)	(0.014)	(0.003)	(0.003)
Other Controls	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,698	4,241	1,294	1,231	3,404	3,010
Adjusted R^2	0.064	0.070	0.098	0.102	0.024	0.031

Notes: (1) The table reports the OLS regression results for Equation (1.3). (2) No survey weights are applied. (3) All the independent variables are measured as of year 2014, except for the minimum wage dummy which is taken from the 2015 survey. (4) The independent variables, Employment and Labor Productivity are all in log values. High-skilled Labor is the share of employees with a university degree. Minimum Wage is a dummy variable which equals one if the plant raised wages due to the minimum wage regulation in 2015. Exporter, Demand for Training, and Skilled Labor Shortage are dummy variables for the exporter status, whether a plant experienced staffing problems that demand for further training, and whether a plant reported skilled workers hard to find, respectively. (5) Other controls are a set of dummy variables for works council, up-to-date technology, process improvement, high competitive pressure, and foreign ownership. (6) Both industry (2-digit NACE Rev.2) and federal state fixed effects are included. (7) Standard errors are clustered at the 3-digit NACE Rev.2 level and reported in parentheses. (8) *** p<0.01, ** p<0.05, * p<0.1.

Beyond this skill composition channel, the association between plant size and adoption is stronger in the manufacturing sector, whereas in the non-manufacturing sector, this association loses statistical significance when additional controls are included as in Column (6). The introduction of minimum wage is identified to be positively correlated with adoption in the manufacturing sector as in Column (4), consistent with the findings in Fan et al. (2021) based on the Chinese firm-level data. In both sectors, exporter status is positively associated with adoption with the manufacturing exporters seeing a larger effect.

The robust results on exporter status underscore the role of international trade in robotization: since both plant size and productivity are controlled for, the effect of trade on robot adoption perhaps operates through a channel that goes beyond market size and productivity selection. The labor shortage measures, on the contrary, play a much more prominent role in the non-manufacturing sector. In particular, shortage of skilled labor is strongly associated with a lower probability of adoption. These findings, being correlational in nature, indeed suggest that there can be important differences in the determinants of robot adoption between manufacturing and non-manufacturing plants. For instance, as collaborative robots are used more intensively in the non-manufacturing sector, the elasticity of substitution between robots and human workers may depend on the type of robots and thus be different across sectors.

Because the panel dataset of robot use is based on retrospective questions in the 2019 survey, more than 40% of the robot adopters in our sample adopted robots in 2018, while the cross-sectional specification has the base year as of 2014. To address this issue, and also to better exploit the timing information of robot adoption, we construct a panel dataset by dividing the sample period equally into two two-year windows. The regression specification is given by

$$\mathrm{RobotAdp}_{ijk}^{t+1,t+2} = \alpha + X_{ijkt}\beta + \phi_{jt} + \psi_{kt} + \varepsilon_{ijkt}, \tag{1.4}$$

where the base year t is 2014 for the first period and 2016 for the second period and $\mathrm{RobotAdp}_{ijk}^{t+1,t+2}$ is a dummy variable which equals one if a plant that does not use robots in base year t newly adopts robots in the two subsequent years. Since our sample is now a stacked two-period panel, we also include industry-period and state-period fixed effects ϕ_{jt} and ψ_{kt} to absorb any industry- or state-specific time trends. We drop all the plant-period pairs if a plant uses robots in or prior to the base year of a given period. Therefore, if a plant adopts robots in the first period, its second-period observation is excluded from our sample.

Table 1.7: Correlates of Robot Adoption: Panel Specification

	Dependent Variable: Robot Adoption Dummy					
	Full Sample		Manufacturing		Non-Manufacturing	
	(1)	(2)	(3)	(4)	(5)	(6)
Employment	0.005***	0.004***	0.017***	0.012***	0.001**	0.001*
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
High-Skilled Labor	-0.013***	-0.016***	-0.074***	-0.074***	0.001	0.001
	(0.005)	(0.006)	(0.021)	(0.022)	(0.004)	(0.005)
Minimum Wage	0.002	0.004	0.008	0.015**	-0.000	-0.001
	(0.003)	(0.003)	(0.007)	(0.007)	(0.002)	(0.002)
Exporter	0.016***	0.015***	0.017***	0.017***	0.007*	0.007*
	(0.003)	(0.004)	(0.007)	(0.007)	(0.004)	(0.004)
Demand for Training	0.008*	0.008*	0.019	0.017	0.004	0.005
	(0.004)	(0.004)	(0.013)	(0.013)	(0.003)	(0.003)
Skilled Labor Shortage	-0.005**	-0.004*	-0.006	-0.003	-0.004**	-0.004**
	(0.002)	(0.002)	(0.007)	(0.007)	(0.002)	(0.002)
Other Controls	No	Yes	No	Yes	No	Yes
Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Period FE	Yes	Yes	Yes	Yes	Yes	Yes
N	10,120	9,181	2,814	2,689	7,306	6,492
Adjusted R^2	0.038	0.041	0.059	0.061	0.020	0.024

Notes: (1) The table reports the OLS regression results for Equation (1.4) using the panel that consists of two periods: 2015-2016 and 2017-2018. (2) No survey weights are applied. (3) All the independent variables are measured at the beginning of each period, 2014 or 2016, except for the minimum wage dummy which is taken from the 2015 survey. (4) The independent variables, Employment and Labor Productivity are all in log values. High-skilled Labor is the share of employees with a university degree. Minimum Wage is a dummy variable which equals one if the plant raised wages due to the minimum wage regulation in 2015. Exporter, Demand for Training, and Skilled Labor Shortage are dummy variables for the exporter status, whether a plant experienced staffing problems that demand for further training, and whether a plant reported skilled workers hard to find, respectively. (5) Other controls are a set of dummy variables for works council, up-to-date technology, process improvement, high competitive pressure, and foreign ownership. (6) Both industry-period (2-digit NACE Rev.2) and state-period fixed effects are included. (7) Standard errors are clustered at the plant level and reported in parentheses. (8) *** p<0.01, ** p<0.05, * p<0.1.

Table 1.7 reports the regression results using the panel data. The results confirm all the findings in the cross-sectional specifications for the full sample as well as for the two subsamples. Compared with Table 1.6, the point estimates for the total employment, the share of high-skilled labor, and exporter status are about half of the cross-sectional estimates with the statistical significance being preserved. This is reassuring because we study the effect of plant-level characteristics on adoption in the two subsequent years in the panel specification as opposed to four subsequent years in the cross-sectional specification.

To summarize, we empirically document several plant-level correlates of robot adoption. It should be noted that all the findings that we have discussed so far are correlational in nature. Besides a robust association between plant size and robot adoption, we find suggestive evidence of the task-based channel (high-skilled labor share) and the relative factor price channel (minimum wage introduction) of robot adoption in the manufacturing sector. The findings lend support to the existing theoretical framework of robot adoption in the context of Germany.

1.4 Concluding Remarks

Using a newly collected dataset, we provide the first portrait of the use and adoption of robots at the plant level in Germany. Five stylized facts emerge from our descriptive analysis. First, robot use is still relatively rare. Second, the distribution of robots is highly skewed. Third, plants that adopt robots for the first time contribute substantially to the recent wave of robotization. Fourth, robot users are different from non-users. Fifth, the difference between robot users and non-users hinges on the type of robots in use. We view the stylized facts we document as an integral part of the ongoing investigation of robotization across countries at the microeconomic level. Going beyond the descriptive analysis, we further examine the correlates of robot adoption and document plant size, skill composition, the minimum wage introduction, exporter status, and labor shortage to be correlated with robot adoption in the subsequent years.

We also provide evidence of how the association between those plant-level characteristics and robot adoption varies between the manufacturing and non-manufacturing sector.

Our empirical results point to several open questions. First, in light of the existing theories of technology diffusion, it would be of direct theoretical and policy relevance to examine the dynamic diffusion process of robotic technologies at the micro level. Second, it is natural to ask whether the correlates of robot adoption we have documented indeed causally impact plants' adoption decisions. Micro-level causal evidence in this regard will be highly informative for policymakers. Last, and perhaps most importantly, as the theoretical literature mostly focuses on the medium- and long-run implications of robots on growth and labor share (Ray and Mookherjee, 2022), with the continued effort of data collection, we envisage that one would be able to shed light on those important theoretical questions by going beyond the short-term effects of robot adoption.

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Appendix

A1.1 Survey Questions

We provide below a word-to-word English translation of the section on robot use in the 2019 IAB Establishment Survey.

Question 77.

a) Have you used robots over the last 5 years for operational performance or production? [*A robot is any automated machine with multiple axes or directions of movement, programmed to perform specific tasks (partially) without human intervention. This includes industrial robots but also service robots. This excludes machine tools, e.g. CNC-machines.*] Yes/No.

If so:

b) How many robots have you used in total over the last five years? An estimation will suffice. If more robots are used in one robot cell, please count them individually. An estimation will suffice. [Interviewer: If "none" enter "0". Please enter "XXXX" if there is no information possible to single years.]

If in 2018 no use of any robot or no information possible, go to question 81. If there was use of at least one robot in 2018, go to question 78.

Question 78.

If there was use of at least one robot in 2018: How many of the robots used in 2018 were purchased at a price of less than 50,000 Euros? Please – if possible – consider only the purchase price, without any further costs for tools or the integration of the robots into your production circle.

Question 79.

How many of the robots used in 2018 are separated from employees during the regular operations with the help of a protection device, e.g. cage, fence, separate room, light barrier or sensor mat?

Question 80.

How many of the robots used in 2018 did you just purchase in 2018?

A1.2 Robotization Premia on the Intensive Margin

In the paper, we have tackled robotization premia on the extensive margin. Since the survey dataset has the robot count at the plant level, we can also examine, within the sample of robot users, robotization premia on the intensive margin. We consider, analogous to Equation (1.1), the following regression specification:

$$X_{ijk} = \alpha + \beta \log(\text{Robot}_{ijk}) + \phi_j + \psi_k + \gamma \log(\text{Emp}_{ijk}) + \varepsilon_{ijk}, \tag{1.5}$$

where log(Robot) is the log number of robots in a given plant in 2018.

Table A1.1 reports the estimates of β for intensive margin regressions. The upper panel includes industry and state fixed effects and the lower panel includes additionally the plant size control. Since employment is used as a control variable, the point estimate for employment in the lower panel drops out. According to the upper panel, plants that install more robots are larger, have higher labor productivity, and pay higher wages. Column (1) suggests that a 10% difference in robot stock is associated with a 3.96% difference in plant size measured by employment. In connection with Fact II, it also implies that the high concentration of robots is likely to be driven by larger plants. However, once plant size is controlled for as in the lower panel, the regression results are inconclusive. We do not find strong evidence of differences in plant-level characteristics other than employment between different robot users.

Moreover, to study the role of robot heterogeneity in the intensive margin, we incorporate into Equation (1.5) the share of cage robots and the share of expensive robots and report the estimation results based on the sample of robot users in Table A1.2. The two new variables enter the regression positively and significantly in Column (1), suggesting the additional plant size premium associated with the use of cage or expensive robots. According to the point estimates, conditional on the plant-level robot stock, a plant that solely uses cage robots is 82.6% ($e^{0.602} - 1 \approx 0.826$) larger than a plant that only uses non-cage robots, and a plant that solely uses expensive robots is 57.0% ($e^{0.451} - 1 \approx 0.570$) larger than a plant that only uses cheap robots. Consistent with the extensive margin result, a larger share of cage robots to be associated with a higher probability to export.

Table A1.1: Robotization Premia: The Intensive Margin

	Dependent Variable					
	Employment	Labor Productivity	TFP	High-Skilled Labor	Wage	Exporter
	(1)	(2)	(3)	(4)	(5)	(6)
log(Robots)	0.396***	0.073***	-0.039	0.005	0.067***	0.013
	(0.082)	(0.028)	(0.031)	(0.005)	(0.018)	(0.017)
Plant Size	No	No	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	533	377	210	385	323	501
Adjusted R^2	0.437	0.320	0.375	0.335	0.458	0.311
log(Robots)			-0.022	-0.001	0.012	-0.014
			(0.037)	(0.005)	(0.014)	(0.019)
Plant Size	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	533	377	210	385	323	501
Adjusted R^2	0.437	0.376	0.375	0.357	0.552	0.341

Notes: (1) The table reports the OLS regression results for Equation (1.5). (2) No survey weights are applied. (3) The dependent variables, Employment, Labor Productivity, TFP, and Wage, are all in log values. Exporter is a dummy variable. High-Skilled Labor is the share of employees with a university degree. (4) Both specifications are based on the full sample of robot users in 2018. The first specification includes industry (2-digit NACE Rev.2 industries) and state fixed effects. The second specification includes both fixed effects and plant-level employment (in log). (5) Standard errors are clustered at 3-digit NACE Rev.2 level and reported in parentheses. (6) *** p<0.01, ** p<0.05, * p<0.1.

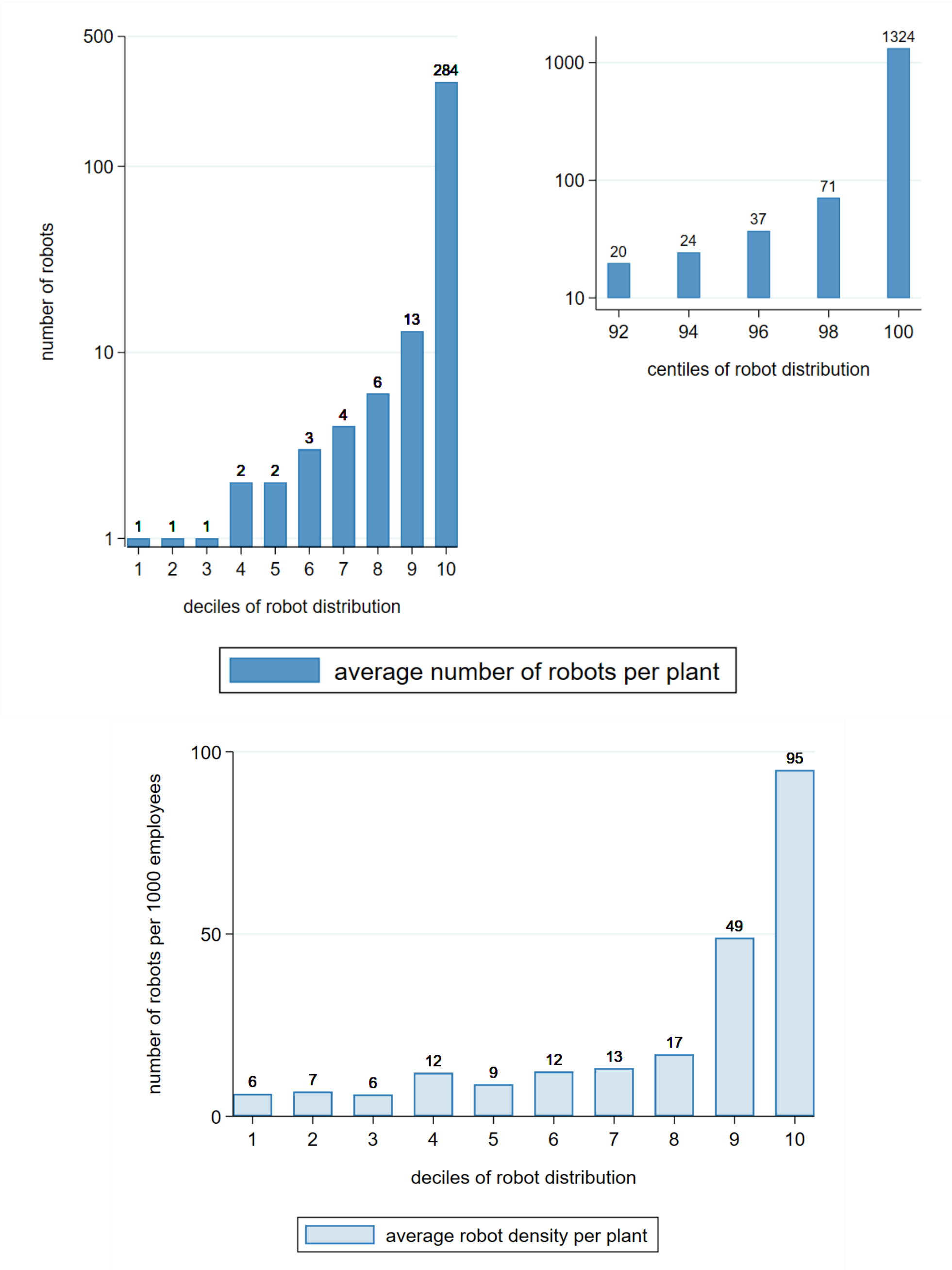
Table A1.2: Robotization Premia: Heterogeneity in the Intensive Margin

	Dependent Variable					
	Employment	Labor Productivity	TFP	High-Skilled Labor	Wage	Exporter
	(1)	(2)	(3)	(4)	(5)	(6)
log(Robots)	0.389***	0.019	-0.016	-0.002	0.008	-0.014
	(0.091)	(0.027)	(0.043)	(0.005)	(0.016)	(0.020)
Share of Cage Robots	0.602***	0.013	-0.043	-0.020	0.011	0.119**
	(0.163)	(0.105)	(0.185)	(0.020)	(0.077)	(0.055)
Share of Expensive Robots	0.451**	0.030	0.018	-0.007	-0.048	0.005
	(0.180)	(0.063)	(0.126)	(0.018)	(0.056)	(0.041)
Plant Size	No	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	493	360	206	362	313	473
Adjusted R^2	0.460	0.389	0.357	0.361	0.534	0.344

Notes: (1) This table reports the OLS regression results for Equation (1.5) with the share of different types of robots being incorporated. (2) No survey weights are applied. (3) The dependent variables, Employment, Labor Productivity, TFP, and Wage, are all in log values. Exporter is a dummy variable. High-Skilled Labor is the share of employees with a university degree. (4) All regressions are based on the full sample (both manufacturing and non-manufacturing plants included) and include both 2-digit NACE Rev.2 industry and federal state fixed effects and the employment count (in log) as controls. (5) Standard errors are clustered at 3-digit NACE Rev. 2 level and reported in parentheses. (6) *** p<0.01, ** p<0.05, * p<0.1.

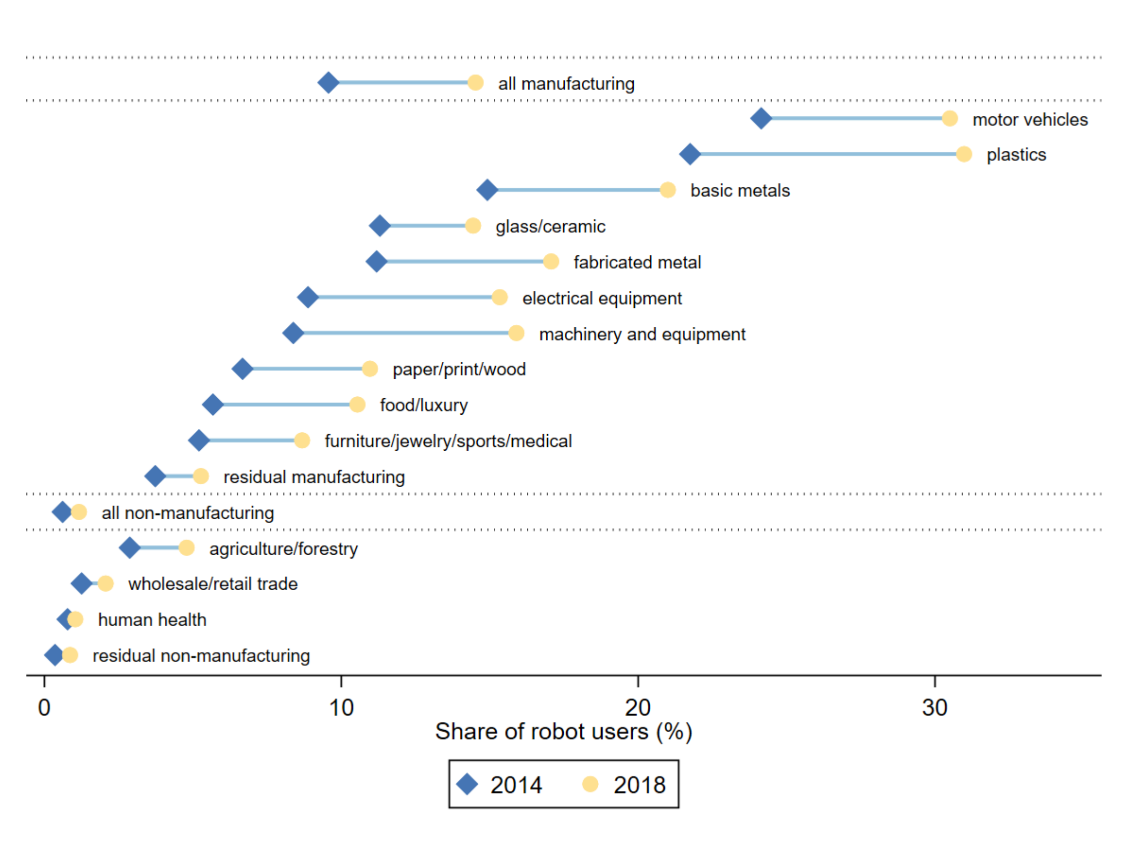
A1.3 Additional Figures

Figure A1.1: Distribution of Robots in Manufacturing in 2018 (without Survey Weights)



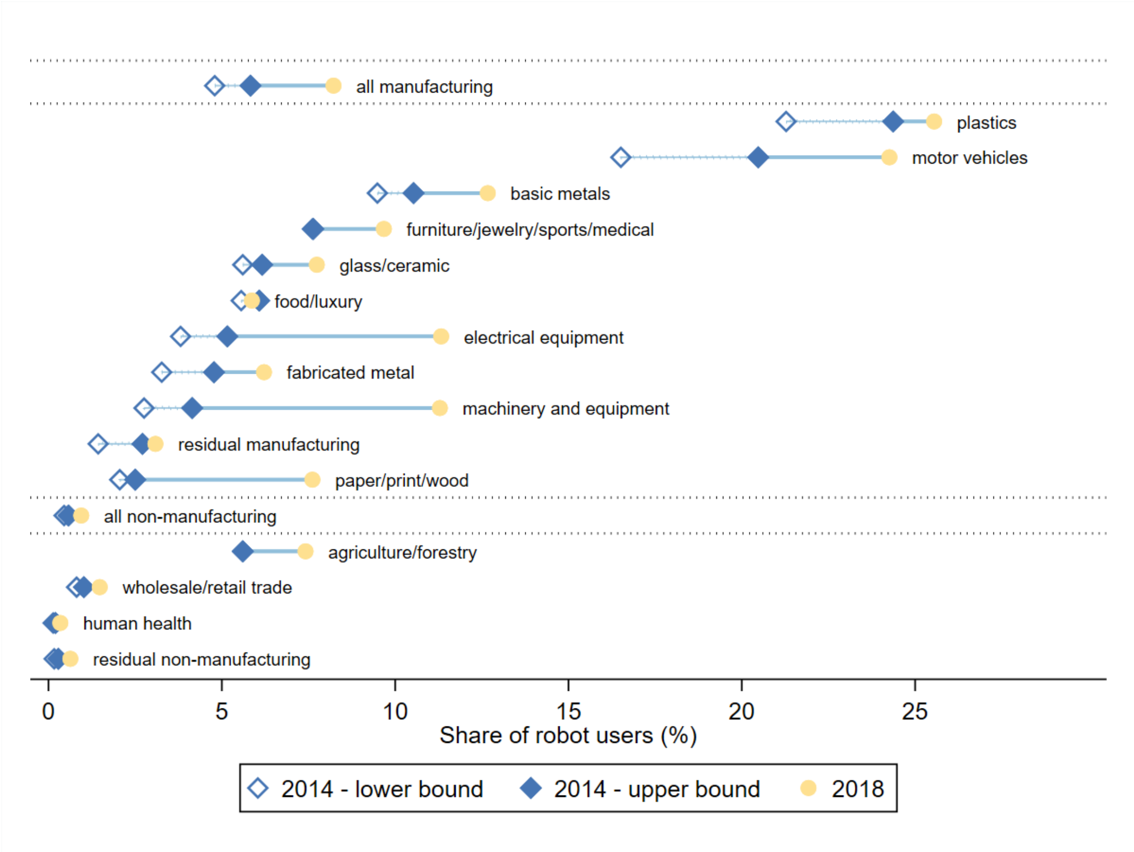
Notes: (1) We sort plants by the number of robots reported in 2018. For plants with the same number of robots, they are randomly sorted (a further sorting by plant-level attributes like plant size could artificially skew the distribution of robot intensity). The same sorting is applied to both panels. (2) No survey weights are applied. (3) Average robot count or robot density (measured by robot count per 1,000 employees) is calculated within each decile or bi-centile and rounded to the closest integer. (4) Due to skewness of the distribution, the first panel is plotted in log scale.

Figure A1.2: Share of Robot Users: 2014 versus 2018 (without Survey Weights)



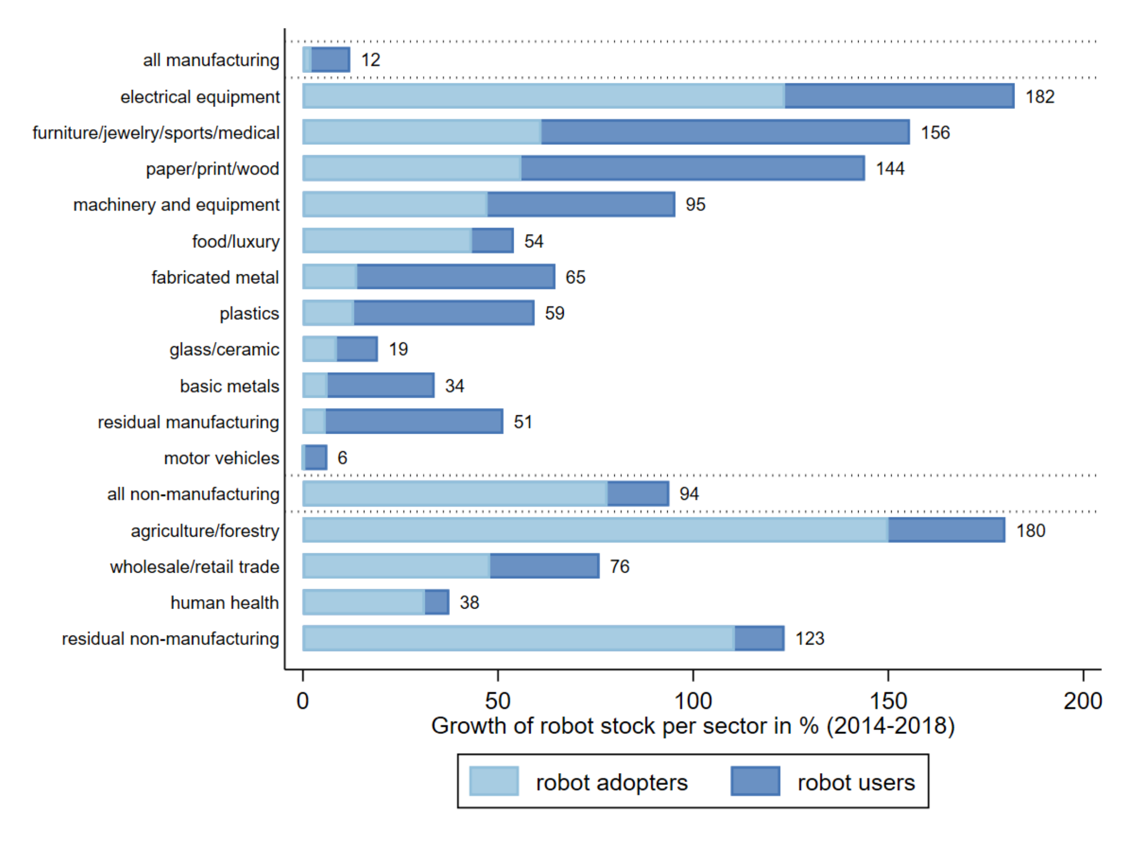
Notes: (1) No survey weights are applied. (2) A plant is identified as a robot user in 2018 if it answered yes to the question of whether it used robots from 2014 to 2018 and its robot stock in 2018 was not zero. (3) The estimated share of robot users in 2014 is the product of the share of robot users in 2018 and the share of plants reporting a positive robot stock in 2014 in the robot users in 2018 reporting a non-missing robot stock in 2014. (4) The industries included in the figure are based on the 2-digit IAB Establishment Panel Survey classification (aggregated from 2-digit NACE Rev.2 industries). Due to very few observations of robot users, the following industries are combined into a residual manufacturing category: textiles/clothing, repair/installation, precision/optical equipment, and chemical/pharmaceutical.

Figure A1.3: Share of Robot Users: 2014 versus 2018 (Lower and Upper Bounds)



Notes: (1) Survey weights in 2018 are applied. (2) A plant is identified as a robot user in 2018 if it answered yes to the question of whether it used robots from 2014 to 2018 and its robot stock in 2018 was not zero. (3) The lower bound for the share of robot users in 2014 is based on the share of plants stating their robot stock being positive in 2014, assuming missing values to be zero. (4) The upper bound for the share of robot users in 2014 is based on the share of plants stating their robot stock being positive in 2014, assuming missing values to be positive, such that these plants with missing robot stock are counted as robot users in 2014. (5) The industries included in the figure are based on the 2-digit IAB Establishment Panel Survey classification (aggregated from 2-digit NACE Rev.2 industries). Due to very few observations of robot users, the following industries are combined into a residual manufacturing category: textiles/clothing, repair/installation, precision/optical equipment, and chemical/pharmaceutical.

Figure A1.4: Decomposition of Growth in Robot Stock (without Survey Weights)



Notes: (1) Calculations are based on the surveyed plants that reported their robot use in each year from 2014 to 2018. (2) No survey weights are applied. (3) For each industry (sector), the contribution of the robot adopters to growth is defined as the ratio of the total robot stock of robot adopters in 2018 to the robot stock aggregated over the existing users in 2014. The contribution of the robot users to growth is defined as the percentage change of the aggregate robot stock from 2014 to 2018 for the plants that already used robots in 2014. (4) The industries included in the figure are based on the 2-digit IAB Establishment Panel Survey classification (aggregated from 2-digit NACE Rev.2 industries). Due to very few observations of robot users, the following industries are combined into a residual manufacturing category: textiles/clothing, repair/installation, precision/optical equipment, and chemical/pharmaceutical.

Chapter 2

High Wage Firms and Robot Adoption

2.1 Introduction

Advanced automation technologies, such as robots and artificial intelligence, have been increasingly applied worldwide with significant effects on labor markets (Acemoglu et al., 2020; Dauth et al., 2021), firm performance (Bonfiglioli et al., 2020; Dinlersoz and Wolf, 2024; Graetz and Michaels, 2018), and economic growth (Acemoglu and Restrepo, 2018b; Zeira, 1998).[1] In order to form evidence-based expectations regarding the future diffusion of advanced technologies and to develop effective policy instruments respectively, it is crucial to understand the underlying investment decisions of firms.

Importantly, this decision to invest in technologies such as industrial robots takes place at the micro-level, for which data has long been scarce (Raj and Seamans, 2018).[2] Empirical studies have only recently identified determinants of firm-level robot adoption, the most decisive being productivity and firm size (Acemoglu et al., 2020; Deng et al., 2023b; Koch et al., 2021). Further drivers are skilled labor shortage, relative factor price changes, international competitive pressure, and foreign ownership (Deng et al., 2023b; Fan et al., 2021; Gómez and Vargas, 2012; Zator, 2019). Additionally, quality improvements and labor cost savings are reported by firms as substantial motivation behind automation decisions (Acemoglu et al., 2022).

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1. According to the IFR World Robotics 2023 Report the overall long-term growth trend will likely continue. In 2024, annual robot installations worldwide will exceed the number of 600,000 units for the first time (IFR, 2023).
2. An assessment of recent micro-level robot data and associated emerging empirical literature can be found in Deng et al. (2023b). These data sets can generate new insights regarding factor (re-)allocation within sectors that cannot be captured by industry-level data (Plümpe and Stegmaier, 2022).

This paper takes a closer look at the role of labor costs and integration costs in the firm level decision to adopt robots. Thereby, it contributes to the literature on wages and advanced technology use by testing two core assumptions in canonical models of automation regarding relative and fixed costs of technology adoption. Firstly, plants with relatively higher variable labor costs have a larger incentive to change towards a more capital-intensive production.[3] Secondly, there are high fixed integration costs associated with advanced technology adoption, which diminish potential gains from automation.[4] Despite the prominence of these channels in theory, there is limited empirical evidence. Most importantly, Acemoglu et al. (2022) investigates this matter. However, their measure of labor costs is imprecise in light of the theoretical literature.[5] In contrast, this paper provides a more comprehensive empirical assessment by using estimates based on the wage decomposition concept by Abowd, Kramarz, and Margolis (1999), henceforth AKM, which establishes a closer link with economic theory.

In fact, with a task-based model of automation, I describe profitability of advanced technology adoption conditional on relative effective costs of specialized capital and labor.[6] I show that the role of labor costs in the robot adoption decision is theoretically ambiguous, depending on associated changes in labor demand. More precisely, it depends on the differential replaceability of workers across different tasks and the elasticity of substitution between tasks in production. If robots substitute labor in sufficiently many tasks, a firm with a higher firm wage premium has comparatively larger labor cost savings than a firm with a low premium. But if robot adoption requires several additional hires to perform complementary tasks, firms with a high firm wage premium have *ceteris paribus* relatively lower cost savings from robot adoption.

[3] Zeira (1998) describe relative prices of capital and labor as crucial determinants of industrial technology adoption. Similarly, this is formulated in task-based models where technology adoption additionally depends on comparative advantages of capital and labor in production task performance (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018a; Autor et al., 2003).

[4] The literature describes such fixed costs as potential entry barriers to advanced technology use (Leigh et al., 2022), and assumes economies of scale in adoption (Dunne and Schmitz, 1995).

[5] They use micro-level data for the United States but lack respective worker-level data to perform a wage decomposition. Consequently, they have to rely on average wages as a proxy for the firm-specific wage premium.

[6] Modeling the production of goods and services (output) based on units of work activity (tasks) is particularly suitable to describe the nexus of changes in labor market conditions and technology adoption (Acemoglu and Autor, 2011).

Testing respective model implications empirically requires precise measurements of robot use and labor costs, which I obtain from high-quality employer-employee data from Germany. Firstly, I measure potential labor cost savings with the AKM firm-specific wage premium, which captures the part of the wage that a firm pays all its employees regardless of occupation or worker skill (Abowd et al., 2002; Card et al., 2013). This firm-specific component represents the variable labor cost in the model, as opposed to the worker-specific components of the wage – given occupation, skill, and job experience within an industry – that is exogenous from a firm's perspective.[7] This makes the firm-specific premium a superior measure for potential labor cost savings compared to the total wage that includes the exogenous worker-specific wage components. Thus, the decomposition allows the disentangling of labor costs from workforce composition effects.[8]

Secondly, on the technology side, robots are a specifically suitable test case. As process innovations affect the cost side of production (Rubens, 2022), the direct measure of robot use within production units is well-suited for the analysis. Further, compared to previous automation technologies robots can replace human labor to a much larger extent (Autor, 2015), and thus, they can generate significant labor cost savings. Finally, despite declining robot prices in recent decades, robots still remain among the most expensive automation technologies (Leigh et al., 2022). For my empirical analysis this ensures that despite other potential drivers, costs play a substantial role in the observed robot adoption decision.

[7] Note that the AKM firm component captures the possibility that wages in some firms are systematically lower or higher than in other firms within the same industry (Card et al., 2018). For example, within the automotive industry, a high-skilled engineer with 5 years of job experience obtains a certain industry wage, depending on these characteristics. A market-leading firm might pay this engineer a 10 percentage point higher wage than the industry wage, the firm-specific premium.

[8] Empirical studies show that firm wage premia are concentrated in large firms, which economic theory commonly explains with rent-sharing practices, efficiency wages, and compensating wage differentials (Brown and Medoff, 1989; Lochner et al., 2023b; Troske, 1999). Fackler et al. (2021) discusses how different strands of the literature rationalize the existence of firm wage premia (or discounts), including rent-sharing, labor market imperfections, and labor market power. For a literature review on rent-sharing see Card et al. (2018). In this paper, regardless of its source, the firm-specific wage premium is simply used as a proxy for potential labor cost savings.

Combining these wage decomposition measures and production unit level robot use allows for an empirical analysis of the labor cost saving channel in robot adoption on a very granular level, which adds new insights to the existing literature. I find that, on average, across plants, there is no significant relation between the AKM plant effect and the subsequent probability of adopting robots. However, differentiation between incumbent users and newly robot-adopting plants that face high first-time integration costs reveals relevant heterogeneity. In fact, for the latter economies of scale are decisive for the adoption decision, while labor costs play a significant role once these plants are excluded from the sample. Thereby, on average, a one standard deviation increase in the ex-ante plant AKM relates to a 1.7 percentage point larger probability to adopt robots, which is economically sizeable given the unconditional probability of about 10%. Further, among incumbent users potential labor cost savings are significantly positively associated with the quantity of robots used in production, as well as technology deepening. This is suggestive evidence confirming the assumption in the theoretical literature that high first-time adoption costs can be an entry barrier to advanced technology use.

The paper is organized as follows. Section 2.2 introduces the conceptual framework and derives a testable implication. Section 2.3 describes the data set construction, and section 2.4 contains the empirical analysis. Finally, section 2.5 concludes.

2.2 Conceptual Framework

I build on the conceptual framework by Acemoglu and Autor (2011) and Acemoglu and Restrepo (2022) to guide my empirical analysis. Thereby, I focus on the firm-level decision to perform a certain production task with one of the input factors, labor or specialized capital (robots), under the principle of output maximization. It shows that robot adoption is conditional on a certain productivity threshold that enables a firm to pay one-time fixed costs of first-time robot adoption, as well as a certain share of automatable tasks. Above these thresholds, robot adoption depends on the relative effective costs of labor and specialized capital, where the role of labor costs is ambiguous depending on the differential replaceability of workers across different tasks and the elasticity of substitution. As new adopters have to pay additional fixed costs to integrate the new technology into their production process, the relation of the firm wage premium with robot adoption is expected to be stronger for incumbent robot users. In the following, I describe the basic model setup and derive from a firm's profit maximization problem a respective testable proposition regarding advanced technology adoption.

2.2.1 Basic Model Setup

In a partial equilibrium model for a single industry under monopolistic competition, each firm faces the same iso-elastic demand $y_i = \zeta p_i^{-\eta}$, where y_i is the demand for firm i, p_i is the price charged by firm i with its price elasticity $\eta > 1$, and ζ is a demand shifter, that is assumed to be equal across firms to reduce complexity. On the supply side firms perform the same set of tasks to produce output:

$$y_i = A_i \left(\int_0^1 q_i(x)^{\frac{\sigma-1}{\sigma}} dx \right)^{\frac{\sigma}{\sigma-1}} , \tag{2.1}$$

where A_i denotes the factor-neutral productivity of firm i.[9] Tasks are modeled as a continuum and indexed by x, such that $q_i(x)$ is the number of completed task x, and $\sigma > 0$ is the elasticity of substitution between tasks. For each task x a firm chooses one of the input factors capital or labor:

$$q_i(x) = \ell_i(x) + \lambda\, k_i(x) \, , \tag{2.2}$$

where λ is an efficiency parameter that captures the relative productivity of capital and labor.

[9] See Acemoglu and Restrepo (2022) for an explanation of how technological change can enter the production function in terms of uniform factor augmentation, productivity deepening, or automation.

For simplicity I assume λ to be equal across tasks and firms.[10] To account for the fact that not all tasks are technologically automatable I allow $\lambda = 0$ for some tasks.[11]

To explore the differential impact of potential labor cost savings on robot adoption I allow the costs of the input factor labor to vary across firms to a certain extent. Within each industry, there is an industry wage component w that is exogenous from a firm's perspective and captures the outside option. However, there is also a firm-specific wage component ψ_i that depends on the labor supply faced by firm i or its rent-sharing practices. This distinction captures the concept of the AKM wage decomposition, where ψ_i can be interpreted as a pay premium or discount that is equal for all employees within a firm.[12]

If a firm produces not only with labor it faces an exogenous price for the cost of specialized capital r that is common across firms and tasks. On top of these marginal unit costs, a firm has to pay one-time fixed costs for specialized capital in case of first-time adoption.[13] These are information and management costs as implementing an advanced technology requires the accumulation of specific knowledge, as well as organizational costs associated with rebuilding production structures or assembly lines (Bresnahan et al., 2002). Further installation costs of robots include accessories and maintenance, such that estimates on total installation costs vary from 40% to 150% of the purchasing cost of a robot (Hunt, 2012).[14]

In the literature, such first-time adoption fixed costs are described as a potential entry barrier to the use of advanced technologies (Leigh et al., 2022). Thus, a firm needs to reach a certain size/productivity to be able to pay these relatively high fixed

[10] Note that in principle λ could also be modeled as task-specific, i.e. $\lambda(x) = \lambda^k(x)/\lambda^l(x)$, or firm-specific, where the latter could capture differences in worker skill or use of advanced automation technologies as in (Acemoglu et al., 2022). However, adding such complexity would not change the mechanisms discussed in this section.

[11] As in Acemoglu and Restrepo (2022) I assume that input factors have strict comparative advantages over tasks and that in case of the same unit costs, the task would be performed by capital.

[12] Thus, labor costs of a firm can be described as $c_i^l = (w \times \psi_i) \int_0^1 \ell_i(x)dx$. Note that in the following I simplify the notation with $w_i = w \times \psi_i$.

[13] A firm's cost of capital can be noted as $c_i^k = r\,k_i + F$, where $F = 0$ for incumbent users.

[14] Note that total costs are difficult to capture from an accounting perspective. An establishment might not report related expenditures of robot installation such as engineering and programming services, purchases of sophisticated software, or costs for worker training, which can cause systematic errors in data collection (Leigh and Kraft, 2018).

costs of advanced technologies. To discuss the role of such first-time adoption fixed costs F and the firm wage premium ψ_i for the firm-level decision to adopt robots, I describe the respective profit maximization problem and derive a testable implication in the following.

2.2.2 Firm Profit Maximization

The profit function of a firm that only produces with input factor labor ℓ_i is given in equation 2.3, where under symmetry across tasks the production function simplifies to $y_i = A_i\,\ell_i$. For a firm that produces in addition to labor also with specialized capital (robots) the profit function is described in equation 2.4, where θ is the share of tasks performed with capital and $rk_i + F_k$ the respective additional capital costs:[15]

$$\pi_i(\ell_i) = A_i\,\ell_i\,p_i - w_i\,\ell_i \tag{2.3}$$

$$\pi_i(k_i, \ell_i) = A_i\,\left(\theta^{\frac{1}{\sigma}}\,(\lambda\,k_i)^{\frac{\sigma-1}{\sigma}} + (1-\theta)^{\frac{1}{\sigma}}\,\ell_i^{\frac{\sigma-1}{\sigma}}\right)\,p_i - w_i\,\ell_i - r\,k_i - F \tag{2.4}$$

I derive first-order conditions and the respective optimal profit function for each production setting,

$$\pi_i(\ell_i^*) = \zeta\frac{(\eta-1)^{\eta-1}}{\eta^\eta}\left(\frac{A_i}{w_i}\right)^{\eta-1} \tag{2.5}$$

$$\pi_i(\ell_i^*, k_i^*) = \zeta\frac{(\eta-1)^{\eta-1}}{\eta^\eta}\left(\frac{A_i}{(\theta(r/\lambda)^{1-\sigma} + (1-\theta)w_i^{1-\sigma})^{\frac{1}{1-\sigma}}}\right)^{\eta-1}\quad, \tag{2.6}$$

in order to express the change in profits $\Delta\pi_i$ if a firm switches from a labor-only production technology to production with labor and robots (equation 2.7).[16]

[15] In the following equations I focus on operating profits, neglecting the one-time first adoption costs. This allows for discussion of the robot investment decisions for all firms jointly. The fixed costs of adoption as a potential entry barrier to technology use are discussed separately.

[16] Note that by construction these two optimal profit functions are identical if no tasks are produced by capital ($\theta = 0$). See Appendix A2.2 for details.

$$\Delta\pi_i \equiv \zeta\frac{(\eta-1)^{\eta-1}}{\eta^\eta}\left[\left(\frac{A_i}{(\theta(r/\lambda)^{1-\sigma}+(1-\theta)w_i^{1-\sigma})^{\frac{1}{1-\sigma}}}\right)^{\eta-1} - \left(\frac{A_i}{w_i}\right)^{\eta-1}\right] \tag{2.7}$$

Thus, the change in profits then depends on a firm's productivity A_i, its task composition in terms of θ, and the relative effective costs of input factors.[17] Notably, in this simplistic model of robot adoption I focus on the existing automatable tasks that are initially performed by labor in a firm's production process and discuss the potential substitution of labor with capital. Nevertheless, the discussed mechanisms in this section would equivalently apply in a dynamic scenario with firm expansion (new additional tasks).

I assume that a firm only has the incentive to adopt robots if there are *ceteris paribus* profit gains associated, i.e. $\Delta\pi_i > 0$. Importantly, this profitability threshold is relatively larger for new adopters compared to incumbent robot users, as the former's profit gains have to exceed additional first-time technology integration costs.[18] Such profitability thresholds of robot adoption often relate to economies of scale, which has been established in the theoretical and empirical literature (Acemoglu et al., 2020; Autor et al., 2020; Deng et al., 2023b; Koch et al., 2021). In the model, such economies of scale are represented within the productivity term A_i that enters the profit function as a multiplier, and through the first time adoption, fixed costs F that enter the function negatively (see equation 2.4).

Further, it can be shown that there are additional economies of scale in terms of a minimum share of tasks that can be performed by robots.[19] Notably, also among incumbent robot users the automation of additional tasks might require specific investments and knowledge accumulation, which would raise profitability thresholds over-proportionally for smaller plants. To account for such economies of scale in the empirical analysis there will be a particular focus on the role of firm size.

17 Note that effective costs refer to price over productivity of capital and labor. For example, relatively lower effective costs of performing a task with robots can be expressed as: $\frac{r}{\lambda} < w_i$.

18 Note that for adopters the respective threshold is denoted as $\pi_i(k_i, \ell_i) - \pi_i(\ell_i) > F$.

19 There exists a productivity threshold $\bar{A}$ such that firm i adopts robots if its productivity $A_i > \bar{A}$ and a task threshold $\bar{\theta}$ such that firm i adopts robots if it has a certain level of automatable tasks $\theta_i > \bar{\theta}$.

2.2.3 Labor Costs and Profitability of Robot Adoption

Turning to the main aspect of the analysis, I now discuss how labor costs affect the profitability of robot adoption. Therefore, I derive the first order condition ($\frac{\delta \Delta \pi_i}{\delta w_i}$), as noted in Appendix A2.2. In fact, the role of labor costs is theoretically ambiguous, depending on the elasticity of substitution between tasks and the relative effective costs of labor and robots. In the following, I discuss three possible cases that are considered in detail in Appendix A2.2.

Firstly, if the elasticity of substitution between tasks in production σ is sufficiently high ($\sigma > \eta$), profit gains from robot adoption are an increasing function in the firm-specific wage premium ψ_i.[20] In this case, a firm focuses on production with automatable tasks, for which it substitutes labor with robots. Thereby the number of adopted robots hinges on the share of replaceable tasks (θ) and the capacity in task performance per robot. Thus, labor demand declines and the firm saves *ceteris paribus* the respective firm wage premium per displaced worker.[21]

In the other two scenarios, the elasticity of substitution between all tasks in production is relatively low ($\eta > \sigma > 1$), such that robot adoption might raise the demand for complementary (non-automatable) tasks. Thus, a robot-adopting firm saves labor costs for replaced tasks but faces higher labor costs for complementary tasks. Which of these opposing mechanisms predominates depends on the relative effective costs of capital and labor.

In fact, in the second case, effective costs of robots are only *slightly* smaller than those for labor ($r/\lambda < w_i$), such that changes in a firm's labor demand would be relatively small. Respective profit changes due to robot adoption would be an increasing function in labor costs. In contrast in the third case, effective costs of robots are *drastically* smaller than those for labor, leading to huge changes in labor demand for complementary

[20] Note that for the proof in Appendix A2.2 I simplify in the notation with $w_i = w \times \psi_i$.

[21] Note that employment does not necessarily have to decline for this mechanism to be valid. Alternatively, a growing firm might reduce the number of new hires alongside robot adoption. For each worker that is not hired due to an installed robot, firm i would save the respective opportunity costs in the form of ψ_i. This scenario would be more realistic given existing empirical evidence, that finds positive employment effects associated with robot adoption (Deng et al., 2023a).

tasks. Thus, the incentive to adopt robots could also be lower for firms with a higher firm wage premium ψ_i. This theoretical ambiguity is summarized in proposition 1.

Proposition 1. *The impact of labor costs on profit changes is theoretically ambiguous and depends on how the demand for labor changes with robot adoption.*

1. *If the elasticity of substitution between tasks σ is sufficiently high, i.e. $\sigma > \eta > 1$, profit changes from robot adoption are an increasing function in a firm's wage premium ψ_i, i.e. $\frac{\delta(\Delta\pi_i)}{\delta\psi_i} > 0$.*

2. *However, if $\eta > \sigma > 1$, the relation becomes ambiguous. If effective costs of capital are marginally smaller than those for labor ($r/\lambda < w_i$), profit changes are still an increasing function in ψ_i.*

3. *But if effective costs of capital are substantially smaller than those for labor then the effect of ψ_i on θ is large (complementary tasks), such that high ψ firms have a lower incentive to adopt robots, i.e. $\frac{\delta(\Delta\pi_i)}{\delta\psi_i} < 0$.*

Note that even if the effect of labor cost savings on operating profits is positive, first-time integration costs can diminish gains from automation for plants that newly install robots. Thus, if the net effect of the firm wage premium on the incentives of robot adoption is positive, it likely reflects intensive margin adjustment in robots among the incumbent users, while the firm wage premium might play a minor role in the first-time adoption decision.

Altogether, the theoretical ambiguity in proposition 1 requires an empirical investigation of the relation of the ex-ante firm wage premium with robot adoption. Consequently, the following analysis tests if potential labor cost savings can explain subsequent extensive and intensive margins of robot use. Thereby, it is distinguished between adopters with high first time integration costs and incumbent users. In light of the model, a positive association between the firm-specific premium and subsequent (stronger) increase in robot use can be interpreted as evidence that the labor cost saving channel plays a significant role in the micro-level decision to adopt robots.

2.3 Data

For the empirical analysis, I combine plant-level and worker-level data from the Institute for Employment Research (IAB). This section describes the construction of the final data set which links information from the IAB Establishment Panel Survey (wave 2019) with the IAB Employment History (2010-2019), the German Qualification and Career Survey (wave 2012), and estimated establishment fixed wage effects provided by the IAB Research Data Center. Subsequently, summary statistics of the final sample are presented, as well as descriptive evidence on the relation of robot use, firm wage premia, and plant size.

2.3.1 Data Sources

Firstly, the information on robot use is taken from the 2019 wave of the IAB Establishment Panel, a high-quality annual survey of nearly 16,000 plants that is representative at the national and sector levels, as well as for plant-size classes and across German federal states.[22] The respective survey section gives a precise definition of a robot as *any automated machine with multiple axes or directions of movement, programmed to perform specific tasks (partially) without human intervention.*[23] Further, it specifically includes service robots and excludes other advanced automation technologies such as CNC machines.[24]

This plant-level robot use data is linked via unique identifiers (idnum) to administrative worker-level data from the IAB Employment History (BeH), which contains all employment spells of workers subject to social security contributions.[25] This allows

[22] The sample is drawn from the population of German plants that have at least one employee who is subject to social security contributions. For further information on the IAB Establishment Panel, see Bechmann et al. (2019).

[23] This is close to the ISO 8373:2021 definition of a robot: An *automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment.* Robots and robotic devices – Vocabulary; `https://www.iso.org/obp/ui/#iso:std:iso:8373:ed$-$3:v1:en`.

[24] For more details on the survey design and quality of the robot data, see Plümpe and Stegmaier (2022).

[25] The BeH is the main data source behind the publicly available SIAB data described in Frodermann et al. (2021).

me to track employment and wages per plant in years previous to 2019, regardless of whether a plant has been surveyed in the IAB EP before. Within the BeH I select employment spells that cover the cutoff date of June 30 each year and keep the employees subject to social security contributions without special characteristics (group 101). In case of multiple employers I select the highest income spell of a worker.[26] From this data source, I utilize measures for overall employment, full-time employment, and employees' daily wages that I further aggregate as mean daily wage per plant.

Additionally, I link via unique plant identifiers (betnr) the data on estimated establishment fixed wage effects provided by the Research Data Center (FDZ) at the IAB. The underlying estimation strategy is based on Abowd et al. (1999) and Card et al. (2013) and described in Lochner et al. (2023b).[27] The respective data source is the BeH and the plant AKM effects are estimated for five 7-year intervals, of which I use only the 2007−2013 plant-level AKM-values that precede the information on robot use (2014−2018).[28] This estimated establishment fixed effect represents the proportional pay premium (or discount) that is paid by an establishment between 2007-2013 to all of their employees, regardless of any individual-level characteristics of workers (Lochner et al., 2023b). The latter are part of the estimated AKM person effects, which I aggregate per plant and year for the plant-level analysis. This *average* worker AKM effect per plant is included in regression as control for worker quality.

Based on the IAB EP survey questions about whether a plant used robots between 2014 and 2018 (Q77a) and the number of robots used in each year from 2014 to 2018 (Q77b), I define several outcome variables. On the extensive margin, I define a dummy for robot stock increase during the sample period that is equal to 1 if a plant has a higher robot stock in 2018 than in 2014, and equal to zero otherwise.[29] Thereby a robot stock increasing plant can be either a new adopter, that did not use robots in 2014, or

[26] Note that these data preparation steps are standard in the literature working with these data sets, see e.g. Card et al. (2013) or Fackler et al. (2021), and similarly applied by Lochner et al. (2023a) before estimating AKM effects, as described in the following.

[27] For further information on estimation procedure see and data access see also the methodological report by Lochner et al. (2023a), which is extending the original version by Card et al. (2015).

[28] The time dimension is discussed further below, alongside definitions of robot use.

[29] As less than 2% of observed robot users decrease their robot stock in this sample I neglect the option of a negative change in robot stock here.

an incumbent user, that used robots in 2014 and further increases its robot stock.[30] As intensive margin measures, I create variables for the robot stock per plant per year (Q77b) and the change over time as the first difference in robot stock between 2014 and 2018. Similarly, I compute the level and change in robot intensity, i.e. the number of robots per 1000 employees. These definitions enable a discussion on the relation of firm wage premia with robot use with respect to the timing of technology adoption.

To address heterogeneity in robot adoption patterns I additionally use the IAB EP survey questions regarding types of robots (Q78 and Q79).[31] Thereby, I define a plant as *new cage robot adopter*, if a plant increased its robot stock from zero robots in 2014 to a positive number of robots by 2018 and reports for 2018 the use of at least 1 robot, that is separated from employees through a cage or other protection devices. Equivalently, I define a *new expensive robot adopter* if it starts to use robots within the sample period 2014 to 2018 and reports at least 1 robot with a purchasing price above €50,000. These definitions capture variation in robot installation costs, which are assumed to be particularly high for new cage robot adopters that have to reorganize their production process when first installing such industrial robots that are separated from employees during operation.

Finally, I use information on task performance from the 2012 wave of the German Qualification and Career Survey (QAC), which is a large worker survey conducted every six or seven years by the Federal Institute for Vocational Education and Training (BIBB) in cooperation with the Federal Institute for Occupational Safety and Health (BAuA).[32] It contains detailed information on tasks performed and worker occupation and is representative at the national level. Within this survey, I identify tasks that

30 Note that for new adopters respective AKM estimates are considered exogenous as they are measured ex-ante to the first time adoption event. However, for incumbent users the AKM values are only precedent to the latest robot installations, while previous robot installations might have impacted the development of plant wage premia over time. Thus, the analysis differentiates between new adopters and incumbents.

31 In particular, Q78 refers to the purchasing price, i.e. *how many of the robots used in 2018 were purchased at a price of less than €50,000?* Survey question Q79 concerns protection devices, i.e., *how many of the robots used in 2018 are separated from employees during the regular operations with the help of a protection device, e.g., cage, fence, separate room, light barrier, or sensor mat?* For a discussion of these survey questions see Plümpe and Stegmaier (2022).

32 See Rohrbach-Schmidt and Hall (2013) for a description of the data.

are more likely to be performed by robots, e.g., based on questions regarding work demands regarding routine task content (F411_03), high task efficiency (F411_07), or type of work (F303, F305, F308), similarly used as in Deng et al. (2023a).[33]

Based on these selected tasks, I create indicators on 3-digit occupational level (KldB2010) that are each weighted by the frequency of task performance and are supposed to capture the share of (i) routine tasks, (ii) routine manual tasks, and (iii) efficient tasks. I merge these indicators from the QAC to the BeH via 3-digit occupation codes (KldB2010) per industry (WZ2008, 2-digit) to the worker-level data (BeH). Then, I calculate for each of the task indicators, that are assigned to workers based on occupation and industry, the plant-level average. Thus, based on the occupational composition of a plant, I identify its potential for robot use, which I add as an additional control variable in robustness checks.

2.3.2 Descriptives

Table 4.1 presents basic summary statistics for the baseline sample of 1606 manufacturing plants with at least 20 employees. In panel A, I differentiate by the main outcome variable of robot stock increase between 2014 and 2018 (yes/no); in panel B, I distinguish between first-time adopters and incumbent robot users. For each of these groups I depict across columns the mean with its standard deviation and the median for the variables of interest.

Panel A shows that plants that increase their robot stock are initially larger than the non robot stock increasing group with on average around 400 compared to 150

[33] For example, the work demand for routine tasks is captured by question F411_03, which asks *how often does it happen in your job that you have to repeat the same step in every detail?* However, not all routine tasks can be performed by robots, such that additionally questions on the type of work performed are used, including manufacturing, producing goods and commodities (F303), monitoring, control of machines, plants, technical processes (F305), and transporting, storing, shipping (F308). Alternatively, I consider question F411_07 regarding high task efficiency demand that asks *How often does it happen in your job that you have to produce a precise number of items, provide a certain minimum performance, or do a particular work in a specified time?*, assuming that robots would have a comparative advantage in such tasks.

employees.[34] They have a plant AKM effect in 2007 to 2013 that is more than twice as large as for the non-expanding group (on average .52 compared to .24 and at median .63 compared to .28). Also, in terms of average daily wages robot stock increasing plants paid in 2013 at median 10€ more per employee than the non-adopting group of plants. The AKM worker effect in 2013 is slightly lower at mean and median for plants that increase the robot stock, while their share of routine manual tasks in 2013 is slightly larger at .16 percent.

Panel B displays that incumbent users that already used robots in 2014 are, on average, more than twice as large as newly adopting plants.[35] Further, incumbents paid ex-ante a higher AKM firm wage premium (.52 compared to .4 on average) and have a higher worker AKM effect in 2013 on average (.18 compared to .11) and at median (.09 compared to .04). Average daily wages of new adopters are with €95 lower than for incumbents with €99 in 2013. However, in terms of replaceable tasks, part-time employment share and apprenticeship share incumbents and adopters are very similar.

Panel B additionally displays information on the intensive margin of robot use. While new adopters had, by definition, no robots in 2014 and increased them successively until 2018 to an average of 2.1 robots per plant, incumbents had an average of around 50 robots in 2014 and adopted between 2014 and 2018 an average of 5 robots. Normalized by employment the differences are relatively smaller. In fact, robot intensity among robot adopters increases at a median of up to 9 robots per 1000 employees, while for incumbents, median robot intensity rises from 22 to 28 robots per 1000 employees. Notably, the mean-median differences and standard deviations for these intensive margin statistics are very large due to a high concentration of robots in certain plants. This is in line with prior research, as Deng et al. (2023b) show that about half of the total robot stock in Germany is concentrated among the top 5% of robot users.

[34] Note that in a first step, I simply distinguish between plants that increase their robot stock and those that do not. Thereby the latter group includes non-users, as well as incumbents, that do not adopt additional robots between 2014 and 2018. Later on, I differentiate among robot stock increasing plants by initial robot user status in 2014 and compare them with suitable control groups. This is explained further in section 2.5.

[35] Reassuringly, this is in line with empirical evidence from the U.S. where Leigh et al. (2022) find new adopters within the past 5 years to be smaller than earlier adopters.

Table 2.1: Summary Statistics

PANEL A	Robot Stock Increase					
	yes (N=224)			no (N=1382)		
	mean	std dev	median	mean	std dev	median
Employment	398	1130	179	150	946	60
Full-time Employment	357	1058	158	130	856	51
Part-time Employment Share	.09	.12	.05	.13	.14	.08
Apprenticeship Share	.04	.03	.04	.04	.05	.03
AKM plant effect (2007-2013)	.52	.76	.63	.24	.81	.28
Mean AKM worker effect	.15	.59	.14	.16	.81	.14
Median AKM worker effect	.08	.60	.06	.09	.84	.08
Share of routine manual tasks	.16	.03	.16	.15	.03	.15
Mean daily wage per employee	98	27	100	92	30	90

PANEL B	New Adopters (N=107)			Incumbent Users (N=219)		
	mean	std dev	median	mean	std dev	median
Employment	228	235	161	519	2574	142
Full-time Employment	198	2012	132	467	2348	125
Part-time Employment Share	.09	.11	.05	.09	.13	.05
Apprenticeship Share	.04	.04	.04	.04	.03	.04
AKM plant effect (2007-2013)	.40	.87	.44	.54	.73	.62
Mean AKM worker effect	.11	.60	.08	.18	.59	.16
Median AKM worker effect	.04	.62	.03	.09	.62	.09
Share of routine manual tasks	.16	.03	.16	.16	.03	.16
Mean daily wage per employee	95	28	94	99	27	97
Number of robots 2014	0	0	0	50.7	435.5	2
Number of robots 2015	.3	.8	0	51.6	436.4	3
Number of robots 2016	.8	1.2	0	52.5	436.0	3
Number of robots 2017	1.2	1.5	1	54.9	437.5	3
Number of robots 2018	2.1	1.8	1	55.7	434.6	4
Robot intensity 2014	0	0	0	54.8	93.1	22.2
Robot intensity 2015	2.9	9.7	0	57.4	94.0	22.7
Robot intensity 2016	6.9	14.3	0	59.5	95.6	24.6
Robot intensity 2017	10.3	16.7	4.3	64.9	103.9	27.3
Robot intensity 2018	16.6	19.9	9.3	78.5	175.1	28.8
Number cage robots 2018	1.8	1.9	1	56.3	441.1	3.5
Number expensive robots 2018	1.6	1.8	1	8.8	26.7	3
Share cage robots 2018	.9	.4	1	.9	.3	1
Share expensive robots 2018	.7	.4	1	.8	.4	1

Notes: (i) This table reports plant-level summary statistics for the baseline sample of 1606 manufacturing plants with at least 20 employees. (ii) Panel A differentiates by the outcome variable of robot stock increase between 2014 and 2018 (yes/no), Panel B distinguishes between new adopters within the sample period and incumbent users that already used robots in 2014. iii) Employment measures are based on matched employer-employee dataset, AKM estimates are separately provided by the IAB RDC, task data is from QAC, and robot information comes from the IAB EP 2019 wave. iv) For each variable the mean, standard deviation ("std dev"), and median are reported. (v) Variables refer to the base year 2013 unless stated otherwise. (vi) Employment is the number of employees. Part-time and apprentices are reported as a share of total employment. Robot intensity is the number of robots per 1000 employees.

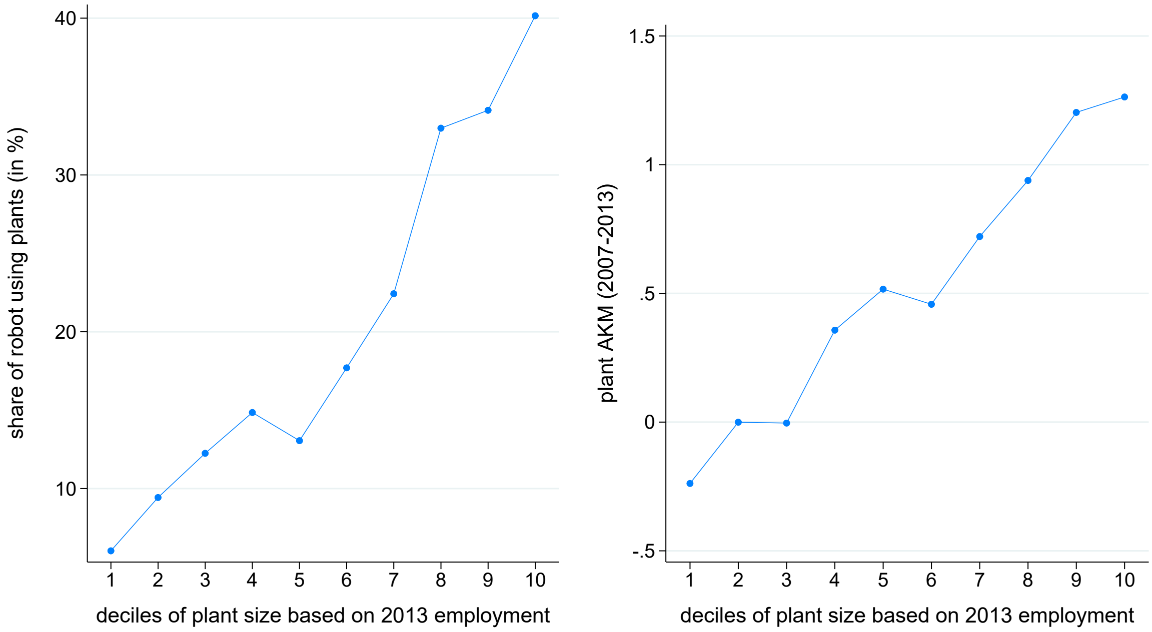

Figure 2.1: Robot Use and Plant AKM across deciles of Plant Size

In terms of heterogeneity of robot types in 2018 (IAB EP survey questions Q78 and Q79), panel B shows that for both groups, about 90% of robots are reported as separated from human workers via a cage or sensor mat, while incumbent users report in the survey 80% of their robots as rather expensive robots with a purchasing price of more than €50.000.

Figure 2.1 sorts plants by employment size in 2013 and depicts in the graph on the left-hand side the share of all robot-using plants per decile for the baseline sample of manufacturing plants with at least 20 employees. Mean values per decile are regression-based and control for industry affiliation. Reassuringly, the relation of plant size and robot use within the sample is positive, and thus, in line with prior research (Acemoglu et al., 2020; Deng et al., 2023b; Koch et al., 2021). In fact, robot use is concentrated at the top of the size distribution. While in the top decile, the share of robot using plants is 40%, for the bottom 50% in the sample, the share is below 15% for each decile.

In addition, the graph on the right-hand side in figure 2.1 confirms that within the sample plant, AKM premia are concentrated in large plants, as discussed in Lochner et al. (2020). It shows that the smallest 30% of plants do, on average, not pay firm wage premia, and the smallest 10% even discount wages.

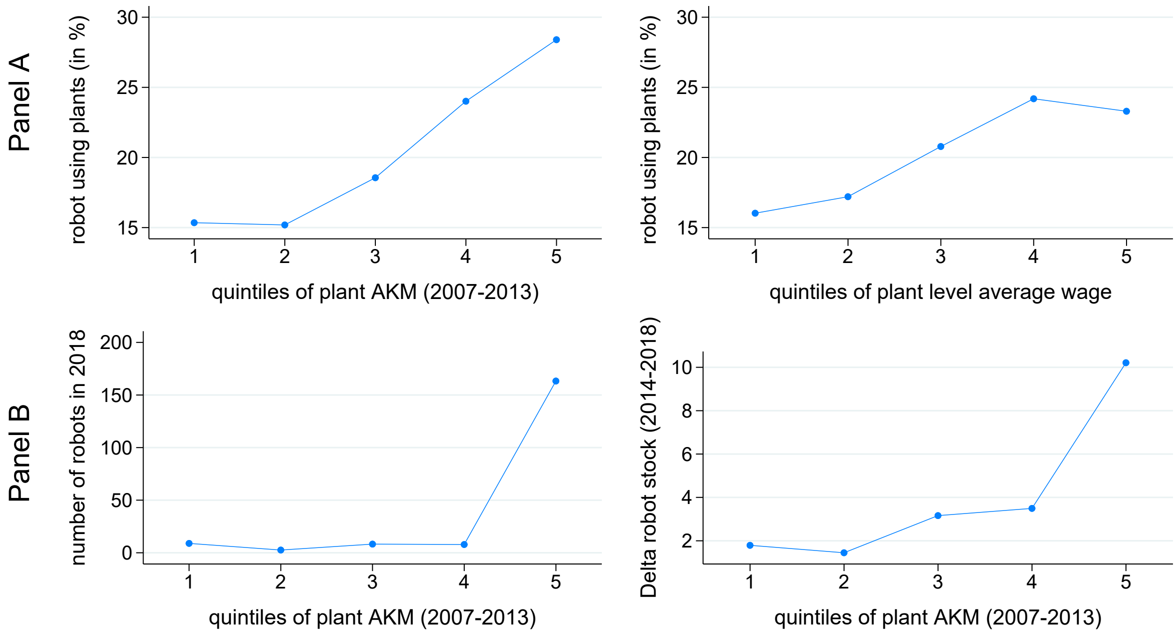

Figure 2.2: Robot Use, Plant AKM (2007-2013), and Average Wage

Finally, figure 2.2 depicts the first descriptive evidence of the relation of the plant AKM effect (2007-2013) with subsequent robot use.[36] Panel A documents in the graph on the left-hand side a positive association between the plant AKM (2007-2013) and the probability of robot use between 2014 and 2018. When, instead, plants are sorted by average daily wages and split into quintiles, the positive relation with robot use remains but is slightly weaker at the top. While among the 20% of plants with the largest plant AKM premium, the share of robot-using plants is almost 30%, the top quintile in terms of average wages is around 5 percentage points lower.

Further, Panel B in figure 2.2 shows for robot using plants the relation of plant AKM with the intensive margin of robot use. The graph on the left-hand side shows that plants in the top quintile have, on average more than 150 robots, while the rest of the plants have, on average, below 5 robots. Also in terms of robot stock growth those with high AKM plants are leading, as they installed on average 10 robots between 2014

[36] Panel B depicts the distribution of robots in 2018 across quintiles of plant AKM. However, results hold across other years of robot use (2014 to 2017).

and 2018, as opposed to 2 robots for the lower 2 quintiles.[37] Altogether, these sample descriptives are in line with previous empirical evidence on the relation of plant size with the firm wage premium, as well as robot use and plant size. The first indication of a positive correlation between the firm wage premium and robot use will be further examined in the next section.

2.4 Empirical Analysis

2.4.1 Empirical Approach

In the following, I describe the different layers of analysis that examine whether potential labor cost savings in the form of ex-ante firm wage premia can explain the probability and quantity of subsequent robot installations at German plants.

2.4.1.1 Firm specific Wage Premium and Extensive Margin Robot Use

Firstly, I test whether the ex-ante AKM firm wage premium can explain robot adoption probability and estimate the following linear probability model:

$$\Delta Robot_{ij}^{2014-2018} = \alpha\, \psi_i^{2007-2013} + X_i'\beta + \phi_j + \epsilon_{ij} \tag{2.8}$$

where the dependent variable is a dummy for robot stock increase at plant i in industry j that is equal to 1 if a plant increases the robot stock between 2014 and 2018, and equal to 0 otherwise. Note that by definition the latter group can include non-robot users, as well as incumbent users that do not increase the robot stock between 2014 and 2018. I specify for each sample selection whether first-time adopters, incumbent robot users, and non-robot-using plants are included, which allows me to examine heterogeneity in adoption patterns, as described more detailed below.

[37] Note that figure 2.2 includes all plants in Panel A (and all robot users in Panel B) without distinguishing between new adopters and incumbent users. Due to small observation numbers of new robot adopters, and high concentration of robots in few plants (Deng et al., 2023b), I cannot present respective estimates for new adopters only. Thus, reversed causality might bias the depicted relations.

The outcome variable is regressed on the AKM firm wage premium (ψ_i) for the period 2007-2013, such that α is the key coefficient of interest.[38] Further, X_i is a vector of plant-level control variables, such as the average worker AKM estimate, that accounts for worker quality and captures, to a certain extent, differences in workforce composition and production structures across firms. This is particularly relevant given that industrial robots can only perform programmable routine-manual tasks that are unevenly distributed across plants. In a set of robustness checks, I additionally include the share of routine manual tasks to test for economies of scale in terms of task composition. However, to a large extent, this task composition effect is captured by the average worker AKM estimate. If anything I expect a stronger relation between the plant AKM and outcome variables for these robustness tests.

As a control for plant size, I include the log number of employees in 2013.[39] To account for differences between incumbent users that display larger variations in robot numbers and new adopters that tend to adopt robots at low margins step by step, I add the 2014 robot intensity as control.[40] Further, dummy variables for works council, collective wage agreement, and labor shortage are included for a subset of regressions to discuss the relation of plant AKM and robot adoption with respect to labor market conditions. Other IAB EP survey-based controls – such as exporter status, foreign ownership, up-to-date technology status, high competitive pressure, and organizational changes — are only included in robustness checks, as panel attrition reduces the number of observations substantially. Finally, ϕ_j are industry dummies (IAB EP variable br19fb19) to control for unobserved industry-specific variation, and ϵ_{ij} is the error term.

[38] Note that the firm-specific wage premium is estimated based on 7-year intervals, as described in section 2.3. Thus, this is a cross-sectional regression with one observation of ψ per firm. In order to relate my findings to existing empirical literature, I additionally use average daily wages as an alternative measure for labor costs in a subset of regressions.

[39] In robustness checks I alternatively use administrative employment numbers for other years (2010-2012), as well as counts of full-time employees.

[40] Table 4.1 displays the average and median number of robots for incumbent users and new adopters per year. While incumbent users, on average, increase their robot stock from 51 robots in 2014 to 56 robots in 2018, or a median from 2 to 4, new adopters start by definition from zero robots in 2014 and slowly increase the stock to 2.1 on average, or 1 at the median, respectively.

In order to account for heterogeneity in adoption patterns I run regressions based on equation (2.8) for specific samples. Firstly, the sample includes all plants to assess the overall robot adoption probability associated with the firm-specific premium for 2007-2013. Secondly, I select only first-time adopters and non-users to test whether potential labor cost savings can explain subsequent first-time robot adoption. Thereby, the time gap between the ex-ante firm wage premium and first-time adoption after the year 2014 allows for a cautious causal interpretation of the relation. Thirdly, I focus on plants that already used robots in 2014 to test whether a higher firm-specific premium is related to subsequent technology deepening. Note that even though for these incumbent users, the firm wage premium is not captured before first-time robot use, their decision to further invest in robots remains a function of relative costs. However, this is not fully exogenous, as particularly productive incumbent users might share productivity gains from previous robot adoption with their employees alongside additional robot installations. Controlling for plant size can address this endogeneity issue to a certain extent. Fourth, I exclude those new robot adopters from the sample that have particularly high first-time integration costs of robots, which allows for a discussion of high fixed costs as barriers to advanced technology use.[41]

Moreover, the analysis pays particular attention to the role of plant size due to its positive relation with the firm wage premium (Lochner et al., 2023b) and robot use (Acemoglu et al., 2020; Deng et al., 2023b; Koch et al., 2021). Besides including in equation (2.8) a size control I address this potential omitted variable bias with several sample selections by plant size. In particular, I run the same regression based on sub-samples, keeping only plants above the median size plant in the sample or excluding the largest 10% of plants respectively. To some extent, these robustness checks allow me to discuss economies of scale. Altogether, with these extensive margin regressions, I empirically test model proposition 1.

[41] This group of new adopters with high integration costs is identified based on the IAB EP survey questions Q78 and Q79, as described in section 2.3. Note that thereby I implicitly assume that information on cage or expensive robot use in 2018 applies also to previous years 2015-2017. However, within the sample first robot adoption is rather lumpy, where new adopters start usually with 1 robot and then increase the stock slowly. Thus, the assumption should hold.

2.4.1.2 Firm specific Wage Premium and Intensive Margin Robot Use

Further, for the sample of robot using plants, I examine the relation of firm wage premia with intensive margin measures of robot use in levels (equation 2.9) and first differences (equation 2.10). The following equations describe respective cross-sectional regression specifications:

$$log(Robots_{ij}) = \alpha\,\psi_i + X_i'\beta \;+\; \phi_j + \epsilon_i \tag{2.9}$$

$$log(\Delta Robots_{ij}) = \alpha\,\psi_i + X_i'\beta \;+\; \phi_j + \epsilon_i \tag{2.10}$$

where $Robots_{ij}$ in equation 2.9 is (i) the number of robots at plant i in industry j or alternatively (ii) the number of robots per 1000 employees ($\frac{Robots_{ij}}{Employment_{ij}}$), henceforth referred to as robot intensity. It estimates the relation of the ex-ante firm specific wage premium (ψ) with the levels of robot stock or robot intensity (separate regressions for years 2014-2018), while the dependent variable $\Delta Robots_{ij}$ in equation 2.10 captures the log difference in robot stock (per employee) between 2014 to 2018. Further, X_i is a vector of plant-level control variables in the year 2013, which includes for all regression specifications the average worker AKM estimate and plant size. Finally, with ϕ_j I add industry dummies and the error term ϵ_{ij}.[42]

To account for heterogeneity on the intensive margin, I distinguish between three samples of robot-using plants. Firstly, I include all robot-using plants to examine whether the firm wage premium can explain subsequent levels and changes in robot use. Secondly, I focus on the sample of incumbent users that already used robots in 2014, for which the model in section 2.2 predicts a stronger association of potential labor cost savings with robot adoption than for new adopters. Thirdly, I select an even more homogeneous sample of incumbent users that increased their robot stock between 2014 and 2018 to investigate whether their technology deepening was accelerated by higher labor costs in the previous period.

[42] For equations 2.8 and 2.9, and 2.10 I additionally run regressions with variables for average daily wage per employee per plant in 2013 to discuss results with respect to Acemoglu et al. (2022).

2.4.2 Empirical Results

, This section presents the empirical results. I find that on average, across plants there is no significant relation between the AKM plant effect and the subsequent probability of adopting robots. However, a heterogeneity analysis reveals that for plants engaged in technology deepening, a significant positive association exists between potential labor cost savings and extensive and intensive margins of robot use. In contrast, for newly robot adopting plants that face high first time integration costs, economies of scale are more decisive for the adoption decision than labor costs.

2.4.2.1 Firm specific Wage Premium and Extensive Margin Robot Use

Table 2.2 depicts the main results for regressions based on the linear probability model in equation (2.8) for various sample selections across panels and columns. Panel A considers all manufacturing plants with at least 20 employees, Panel B includes only relatively larger plants with more employees than the median plant in the sample, and Panel C excludes the largest 10% of plants from the baseline sample. Within each panel, columns 1 and 2 show estimation results based on the sample of all plants; columns 3 and 4 only account for new adopters and non-users, and columns 5 and 6 only for incumbent users.

Baseline extensive margin results in Panel A show a significant positive association between the ex-ante plant AKM and the probability of increasing the robot stock between 2014 and 2018 if only industry affiliation, average worker quality, and robot intensity in 2014 are controlled for (see columns 1, 3, 5).[43] Across all plants a one standard deviation increase in ex-ante plant AKM relates to a 7.2 percentage point higher probability to increase the robot stock. This is economically sizeable given the unconditional within sample probability to use robots of 14%.[44]

[43] Note that robot intensity is not included as control if its variation in the selected sample is very low, e.g. for the sample on new adopters and non-users in columns 3 and 4.

[44] Equivalently, in column (3) a one standard deviation increase is associated with a 3.5 percentage point higher first-time adoption probability in column (5) with a 14.36 percentage point higher probability of incumbent users to deepen their technology use.

Table 2.2: AKM Firm Wage Premia and the Extensive Margin of Robot Use

	Robot stock increase (yes/no)					
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: BASELINE						
Plant AKM	0.0716***	0.0095	0.0348***	-0.0013	0.1436***	0.0438
	(0.0101)	(0.0108)	(0.0093)	(0.0100)	(0.0421)	(0.0405)
Avg. worker AKM	-0.0383***	-0.0489***	-0.0216**	-0.0292***	-0.0966	-0.1435*
	(0.0135)	(0.0143)	(0.0097)	(0.0095)	(0.0657)	(0.0814)
Plant size		0.0981***		0.0640***		0.1211**
		(0.0135)		(0.0100)		(0.0510)
Robot Intensity	0.0019***	0.0018***			0.0005	0.0002
	(0.0004)	(0.0004)			(0.0004)	(0.0003)
N	1587	1587	1386	1386	218	218
Industry	yes	yes	yes	yes	yes	yes
PANEL B: PLANTS WITH ABOVE MEDIAN PLANT SIZE						
Plant AKM	0.0844***	0.0200	0.0415***	0.0013	0.1240**	0.0410
	(0.0134)	(0.0159)	(0.0133)	(0.0146)	(0.0524)	(0.0509)
N	1249	1249	1061	1061	200	200
PANEL C: EXCLUDING LARGEST 10% OF PLANTS						
Plant AKM	0.0304***	-0.0025	0.0072	-0.0123*	0.1350***	0.0586
	(0.0082)	(0.0094)	(0.0067)	(0.0070)	(0.0334)	(0.0391)
N	1340	1340	1198	1198	156	156
Industry	yes	yes	yes	yes	yes	yes
Avg. Worker AKM	yes	yes	yes	yes	yes	yes
Plant Size	no	yes	no	yes	no	yes
Robot Intensity	yes	yes	no	no	yes	yes

Notes: i) Baseline sample in Panel A consists of all manufacturing plants with at least 20 employees in the base year 2013. Panel B splits the sample at the median plant size of the baseline sample, Panel C excludes the 10% largest plants accordingly. ii) All estimations are based on equation 2.8. Columns 1 and 2 include all plants, columns 3 and 4 only new adopters and non-users, and columns 5 and 6 only incumbent users. iii) The dependent variable is a dummy for robot stock increase that is equal to 1 if the number of robots in 2018 exceeds the number of robots in 2014. Plant AKM is the standardized firm wage premium per plant for the period 2007-2013. Average worker quality is measured by the respective average worker AKM effect per plant in 2013. Plant size is the log number of employees in 2013. Robot intensity is the number of robots per 1000 employees in 2014. (iv) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes. *** p<0.01, ** p<0.05, * p<0.1 .

However, accounting for plant size substantially reduces these point estimates in columns (2, 4, 6) with a loss of significance. For the sample of relatively larger plants in Panel B, similar results appear with slightly larger point estimates across columns (1) to (4), and slightly smaller estimates for the incumbent user sample in columns (5) and (6). Additionally, results depicted in Panel C hint at a stronger relation of the firm wage premium with robot adoption among the largest plants, as without the 10% largest plants, α is with 3 percentage points less than half as large as in Panel A (column 1).

Altogether, this indicates an omitted variable bias in columns (1, 3, 5), where coefficient α was largely driven by plant size. Such a decisive role of plant size is expected, given descriptive evidence in Figure 2.1. Moreover, it is in line with existing empirical evidence that finds a concentration of firm-specific wage premia and robots in large plants in Germany (Deng et al., 2023b; Lochner et al., 2023b) and identifies firm size to be the key driver of robot adoption (Acemoglu et al., 2020; Deng et al., 2023b; Koch et al., 2021).

Notably, column (4) in Panel C shows a negative significant relation of the firm wage premium with the probability of first time robot adoption. A one standard deviation increase in the firm-specific premium is associated with a 1.2 percentage point lower adoption probability. In contrast, among incumbent users, coefficient α remains positive and of similar size in Panel C, suggesting that it is not the largest plants driving results regarding technology deepening. The opposite sign of coefficient α for the two subsample estimations reflects heterogeneity in the role of labor costs for robot adoption, which, according to the model, could arise from differential fixed costs.

In order to take a closer look at the role of high costs of first-time robot integration, Table 2.3 presents regression results based on equation 2.8 excluding from the baseline sample first-time cage robot adopters (columns 1 to 6), or alternatively excluding first-time expensive robot adopters (column 7). Column (1) reveals a positive significant relation of the firm wage premium with subsequent robot adoption probability, where a one standard deviation increase is associated with a 1.7 percentage point higher probability to increase the robot stock.[45] This effect is economically sizeable, given the unconditional within-sample probability to use robots of 9.7%. Compared to the respective baseline result (see Table 2.2, column 2 in Panel A) this estimate is larger and now statistically significant at the $\alpha = 10\%$ level. I interpret this as evidence that the labor cost saving channel in the baseline sample is muted by the size channel. Once new cage robot adopters with particularly high integration costs are excluded, for remaining plants, on average, the association of firm wage premia with robot adoption probability becomes significantly positive.

Importantly, these results are robust to including labor market control variables in columns (2)-(5). In fact, controlling for labor market institutions such as collective wage agreements (column 2) and works council (column 3) slightly increases the point estimate for plant AKM, and thus, seems to mitigate the labor cost saving channel for the robot adoption decision. Also, the relation of the ex-ante firm wage premium with robot adoption remains positive and significant if another IAB EP survey-based measure for labor shortage in 2013 is included. If a plant reported issues in finding suitable employees in 2013, the probability of subsequent robot adoption is, on average, 2.8% higher (see columns 4 and 5). Note that a shortage of qualified labor can also lead a plant to pay a higher firm wage premium.

Column (6) focuses on plants with a share of replaceable tasks higher than the median plant, which increases coefficient α to 2.5 percentage points and supports the theoretical assumption on economies of scale with respect to task composition. In light of the model, this can be interpreted as a higher elasticity of substitution between tasks in this selective sample, which reinforces the positive relation compared to column (1). As a robustness test to column (1), column (7) singles out first-time adopters that reported the installation of an expensive robot in 2018 with a purchasing price of more than €50,000. Respective results are slightly weaker and statistically not significant at

[45] Results are qualitatively robust to including administrative employment numbers for other years (2010-2012), as well as counts of full-time employees. They are depicted in Table A2.1.

Table 2.3: AKM firm wage premia, fixed costs, and robot adoption

	Robot stock increase (yes/no)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Plant AKM	0.0169*	0.0196**	0.0171*	0.0174*	0.0200**	0.0250*	0.0141
	(0.0088)	0.0088)	(0.0088)	(0.0093)	(0.0088)	(0.0126)	(0.0090)
Coll. Agreement		-0.0136			-0.0156		
		(0.0182)			(0.0196)		
Works Council			-0.0042		0.0049		
			(0.0126)		(0.0145)		
Labor Shortage				0.0276**	0.0278**		
				(0.0116)	(0.0118)		
N	1529	1532	1531	1512	1507	745	1521
Industry	yes	yes	yes	yes	yes	yes	yes
Worker AKM	yes	yes	yes	yes	yes	yes	yes
Plant Size	yes	yes	yes	yes	yes	yes	yes

Notes: i) The sample includes all manufacturing plants with at least 20 employees in base year 2013, excluding first-time robot adopters that installed industrial cage robots in 2018. Column (1) depicts the main results for this sample selection. The other columns impose additional controls from the IAB EP or sample selection criteria. Column (2) adds as control a dummy for the works council, column (3) a dummy equal to 1 if a plant is bound to a collective agreement, and column (4) a dummy variable for labor scarcity in 2013. Column (5) adds all three control variables at once. Column (6) selects plants based on task composition, excluding those with a share of replaceable tasks below the median. Column (7) is a variation to column (1) and excludes all first-time adopters that installed relatively expensive robots (purchasing price above €50,000). ii) Regressions are based on equation 2.8. The dependent variable is a dummy for robot stock increase that is equal to 1 if the number of robots in 2018 exceeds the number of robots in 2014. Plant AKM is the standardized firm wage premium per plant for the period 2007-2013. Average worker quality is measured by the respective average worker AKM effect per plant in 2013. Plant size is the log number of employees in 2013. (iii) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes.*** p<0.01, ** p<0.05, * p<0.1 .

the $\alpha = 10\%$ level. This suggests that the type of robot is here a better proxy for high fixed costs of first-time adoption than the purchasing price.[46]

Overall, results presented in Table 2.3 are in line with the model and suggest heterogeneity in adoption patterns with respect to firm wage premia and fixed costs.

46 Note that this is in line with previous empirical literature, where besides the purchasing price also installation costs can be decisive for the advanced technology adoption decision (Leigh et al., 2022).

2.4.2.2 Firm specific Wage Premium and Intensive Margin Robot Use

Table 2.4 displays regression results for the sample of robot using plants based on equation 2.9 where the dependent variable is the level of robot use across years 2014 to 2018. The sample varies across panels, starting with all robot-using plants in Panel A, excluding the largest 10% of plants in Panel B, equivalently Panels C and D refer to incumbent users only, and finally, Panel E focuses on the very specific sample of technology deepening plants. All regressions control for industry affiliation, plant size, workforce composition, and robot intensity in 2014.

In Table 2.4, Panel A shows a partly significant positive association of the 2007 to 2013 firm-specific premium with subsequent numbers of robots. For example, a one standard deviation increase in plant AKM is associated with a 15% larger robot stock in 2015, but on average not significantly related to the 2018 robot use in this sample. Panel B reveals that the relation is stronger across all columns and of higher significance if the largest plants are excluded. Panels C and D display that previous results in this table are mainly driven by incumbent users. This corresponds to the discussion in section 2.3 on the concentration of robots and AKM firm wage premia in large plants in Germany, which also persists after controlling for plant size and worker quality. In Panel D, coefficient α becomes even significant with respect to 2018 intensive margin robot use. Finally, Panel E shows for the sample of robot users in 2014 that increased their robot stock in subsequent years. Further, one standard deviation relates on average to a 33-45% higher robot stock.

Equivalently, Table 2.5 reports regression results based on equation 2.9 for log robot intensity as the dependent variable. Overall, patterns remain similar when robot stocks are normalized by employment, which gives more weight to relatively smaller plants. For example, a one standard deviation increase in ex-ante plant AKM is related to a 20% larger robot stock per 1000 employees across all robot-using plants, or to a 32% larger robot intensity among incumbent users, and to a 54% larger robot intensity among technology deepening plants.

Table 2.4: AKM firm wage premium and the size of the robot stock in 2014-2018

	Annual Number of Robots				
	2014	2015	2016	2017	2018
	(1)	(2)	(3)	(4)	(5)
PANEL A: ALL ROBOT USING PLANTS					
Plant AKM (2007-2013)	0.1035	0.1528*	0.1677*	0.1180	0.0397
	(0.0812)	(0.0809)	(0.0920)	(0.1024)	(0.1039)
N (Panel A)	218	241	267	287	325
PANEL B: ALL ROBOT USING PLANTS, EXCLUDING TOP 10% LARGEST PLANTS					
Plant AKM (2007-2013)	0.1615**	0.2316***	0.2350***	0.1744*	0.1485
	(0.0570)	(0.0666)	(0.0810)	(0.0901)	(0.0908)
N (Panel B)	156	168	187	201	228
PANEL C: INCUMBENTS					
Plant AKM (2007-2013)	0.1034	0.1421*	0.1671*	0.1579*	0.1600
	(0.0811)	(0.0776)	(0.0810)	(0.0875)	(0.1075)
N (Panel C)	218	218	218	218	218
PANEL D: INCUMBENTS, EXCLUDING TOP 10% LARGEST PLANTS					
Plant AKM (2007-2013)	0.1932***	0.2293**	0.2467***	0.2393***	0.2313**
	(0.0660)	(0.0824)	(0.0776)	(0.0805)	(0.0908)
N (Panel D)	194	194	194	194	194
PANEL E: INCREASING INCUMBENTS					
Plant AKM (2007-2013)	0.3262**	0.4148***	0.4476***	0.4043**	0.3813**
	(0.1366)	(0.1311)	(0.1396)	(0.1406)	(0.1636)
N (Panel E)	116	116	116	116	116
Industry	yes	yes	yes	yes	yes
Plant Size	yes	yes	yes	yes	yes
Avg. Worker AKM	yes	yes	yes	yes	yes
Robot Intensity 2014	yes	yes	yes	yes	yes

Notes: i) Baseline sample in Panel A consists of all manufacturing plants with at least 20 employees in the base year 2013. Panel B includes only incumbent users who already used robots in 2014; Panel C includes only incumbent users who further increased their robot stock between 2014 and 2018. ii) All estimations are based on equation 2.9. For all columns 1 to 5, the dependent variable is the log number of robots per year for 2014 to 2018, respectively. iii) Plant AKM is the standardized firm wage premium per plant for the period 2007-2013. Average worker quality is measured by the respective average worker AKM effect per plant in 2013. Plant size is the log number of employees in 2013. Robot intensity is the number of robots per 1000 employees in 2014. (iv) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes. *** p<0.01, ** p<0.05, * p<0.1 .

Table 2.5: AKM firm wage premium and plant level robot intensity 2014-2018

	Annual Robot Intensity				
	2014	2015	2016	2017	2018
	(1)	(2)	(3)	(4)	(5)
PANEL A: ALL ROBOT USING PLANTS					
Plant AKM (2007-2013)	0.2536	0.3040*	0.3314**	0.2361*	0.2039
	(0.1719)	(0.1463)	(0.1280)	(0.1241)	(0.1496)
N (Panel A)	218	239	265	284	320
PANEL B: INCUMBENTS					
Plant AKM (2007-2013)	0.2536	0.3190*	0.3565**	0.3132*	0.3223*
	(0.1719)	(0.1726)	(0.1487)	(0.1564)	(0.1802)
PANEL C: INCREASING INCUMBENTS					
Plant AKM (2007-2013)	0.5044***	0.5963***	0.6476***	0.5743***	0.5382***
	(0.1294)	(0.1444)	(0.1081)	(0.1127)	(0.1508)
Industry	yes	yes	yes	yes	yes
Plant Size	yes	yes	yes	yes	yes
Avg. Worker AKM	yes	yes	yes	yes	yes

Notes: i) Baseline sample in Panel A consists of all manufacturing plants with at least 20 employees in the base year 2013. Panel B includes only incumbent users who already used robots in 2014 (N=218), and Panel C includes only incumbent users who further increased their robot stock between 2014 and 2018 (N=116). ii) All estimations are based on equation 2.9. For all columns 1 to 5, the dependent variable is the number of robots per 1000 employees in logs for years 2014 to 2018, respectively. iii) Plant AKM is the standardized firm wage premium per plant for the period 2007-2013. Average worker quality is measured by the respective average worker AKM effect per plant in 2013. Plant size class dummy is included based on the number of employees in 2013; categories are below 50 employees, 50-200 employees, and more than 200 employees. (iv) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes. *** p<0.01, ** p<0.05, * p<0.1 .

Besides a higher level in robot stock, robot users with a relatively higher firm-specific wage premium might also exhibit a stronger growth in robot stock (intensity) between 2014 and 2018. Respective regression results based on equation 2.10 are displayed in Table 2.6. While in Panel A in columns 1 and 2, there is, on average, no significant relation across robot-using plants, for the sample of incumbent users in columns 3 and 4, there is a significant positive association of ex-ante plant AKM with subsequent change in robot stock.

A one standard deviation increase in plant AKM is thereby associated with a subsequent 25% larger increase in robot stock.[47]

Interestingly, the result in column (1) is similar in size and significance to the one in column (3) if I add additional control for occupation-based information on task composition. Taking the sample of robot-using plants and controlling for the share of i) typically programmable manual tasks, ii) the share of routine tasks, or iii) the share of tasks that demand high efficiency reveals a significant positive association of the firm wage premium with increases in robot stock. Thereby, a one standard deviation increase in plant AKM relates to an about 20% larger increase in robot stock. Respective results are depicted in table A2.3.[48]

In column 5 for the sample of robot stock increasing incumbents the association is of larger magnitude and significance with $\alpha = 0.43$. However, Panel B depicts results where the dependent variable in normalized by employment, where only for the sample of robot stock increasing incumbent users in column (5) there is a significant positive relation. In fact, a one standard deviation increase in plant AKM in this sample leads to a 1.8 percent larger number of robots per 1000 employees.

These results presented in Tables 2.4, 2.5, and 2.6 provide empirical evidence regarding proposition 1 on the intensive margin. They suggest that among robot-using plants, the net effect of potential labor cost savings on intensive margins of robot use is positive. Among incumbent robot users, this materializes in the form of larger subsequent levels in robot stock or intensity, as well as a larger growth in robot stock between 2014 and 2018. For the selective sample of robot stock increasing incumbents, these associations are even stronger and additionally display a significant positive relation with changes in robot intensity. This suggests that for plants that deepen their advanced technology use the labor cost saving channel plays a more prominent role.

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[47] This result is robust to including controls for robot intensity 2014, labor market variables, reported competitive pressure and status of technology within the plant, export orientation and plant employment growth, and others. Results are depicted in Appendix Table A2.2.

[48] For detailed definitions of task measures see section 2.3.

Table 2.6: AKM firm wage premium and the intensive margin of robot use

Panel A	Δ Robot Stock				
Plant AKM (2007-2013)	0.0543	0.0435	0.2506**	0.2496*	0.4252**
	(0.1179)	(0.1214)	(0.1111)	(0.1266)	(0.1908)
Robot intensity 2014	yes	yes	no	no	no
Panel B	**Δ Robot Intensity**				
Plant AKM (2007-2013)	0.0057	0.0064	0.0093	0.0098	0.0181*
	(0.0048)	(0.0054)	(0.0006)	(0.0067)	(0.0098)
N	325	228	218	194	116
Avg. Worker AKM	yes	yes	yes	yes	yes
Industry	yes	yes	yes	yes	yes
Plant Size	yes	yes	yes	yes	yes

Notes: i) Baseline sample in column (1) consists of all manufacturing plants with at least 20 employees in the base year 2013 that use robots in 2018. Column (2) excludes the 10% largest plants from the baseline sample and keeps all robot users. Column (3) includes only incumbent users that already used robots in 2014, and column (4) excludes the 10% largest plants from the previous sample. Column (5) includes only incumbent users that further increased their robot stock between 2014 and 2018. ii) Estimations for columns 1 and 2 are based on equation 2.10. iii) The dependent variable is in Panel A, the first difference in robot stock between 2014 and 2018 (IHS transformed), and in Panel B, the respective first difference in robot intensity between 2014 and 2018 (IHS transformed). iv) Plant AKM is the standardized firm wage premium per plant for the period 2007-2013. Average worker quality is measured by the respective average worker AKM effect per plant in 2013. Plant size is controlled for in Panel A with the log number of employees in 2013, and in Panel B with a plant size class dummy based on the number of employees in 2013, which categories are below 50 employees, 50-200 employees, and more than 200 employees. In Panel A it is additionally controlled for robot intensity in 2014 in columns 1 and 2. (v) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

2.4.2.3 Average Wages as Alternative Measure for Labor Costs

To discuss these empirical results in light of the economic literature, I run extensive and intensive margin regressions for an alternative measure of labor cost savings. Table 2.7 displays results based on equation 2.8, where log average wage is used as a proxy for the firm-specific wage premium and the share of replaceable tasks is used to control to some extent for workforce-composition effects. It shows that a 1% increase in average wage relates across plants with a 6.9 percentage point lower probability to increase the robot stock (column 1), or equivalently 7.7 percentage point lower probability if it is controlled for task composition in column (2).[49]

[49] Note that the number of observations declines 2.2 due to missing values in the task measure.

Table 2.7: Log Average Wage and Extensive Margin Robot Use

	Robot stock increase (yes/no)				
	(1)	(2)	(3)	(4)	(5)
Log Average Daily Wage	-0.0694*	-0.0770**	-0.0424*	-0.0640**	-0.1313
	(0.0379)	(0.0334)	(0.0228)	(0.0287)	(0.1439)
Routine Manual Tasks		-0.0325	-0.1211	-0.0081	-0.6520
		(0.1252)	(0.1429)	(0.1239)	(1.2317)
N	1587	1540	1465	1342	210
Industry	yes	yes	yes	yes	yes
Plant Size	yes	yes	yes	yes	yes
Robot Intensity 2014	yes	yes	yes	no	yes

Notes: i) The sample varies across columns. Column 1 is the baseline sample of manufacturing plants with at least 20 employees in the base year 2013. Column 2 excludes from the baseline sample all first-time adopters with high integration costs, column 3 keeps only new adopters and non-users, and column 4 selects only incumbent users. ii) All estimations are based on equation 2.8. iii) The dependent variable is a dummy for robot stock increase equal to 1 if the number of robots in 2018 exceeds the number of robots in 2014. Log average daily wages are based on the BeH data set and measured in 2013. Routine manual tasks are the (IHS transformed) share or routine manual tasks per plant based on the QAC Survey 2012. Plant size is the log number of employees in 2013. Robot intensity is the number of robots per 1000 employees in 2014. (iv) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes. *** p<0.01, ** p<0.05, * p<0.1 .

The negative significant relation remains in columns (3) and (4). If cage robot adopters with high integration costs are excluded in column (3), coefficient α reduces to 4 percentage points respectively. In column (4), where incumbent users are excluded, a one percent increase in average wage per plant is associated with a 6.4 percentage point lower probability of increasing the robot stock. Finally, there is no significant relation between log average wages in 2013 and subsequent extensive margin adoption among incumbent users (column 5).

Thus, I conclude that the measure of average wage shows a negative relation between labor costs and robot adoption on the extensive margin. The AKM wage decomposition reveals that this is likely driven by the worker-specific component (worker quality), while the firm-specific component is positively associated with robot stock increase (compare Tables 2.2 and 2.7). Notably, this difference highlights the importance of the choice of measurement for the analysis in the context of Germany.

Further, I compare estimation results for the wage measure and the firm wage premium regarding intensive margin regressions. Table 2.8 presents a selected set of results, similar to tables 2.4 and 2.5. Panel A shows that across robot-using plants, there is a weak association of the average daily wage in 2013 and subsequent robot stock across years.[50] However, excluding the largest 10% of all plants in Panel B, or equivalently selecting incumbent users except the top 10% largest, leads to a significant positive relation. For example, in Panel B an increase in the average daily wage by 1% is associated with an about 46% larger robot stock for years 2015 to 2017. These intensive margin results for the average daily wage per plant are qualitatively similar to the intensive margin results for firm wage premia (compare table 2.4). In contrast, Panel D shows a weaker (non-significant) association of the wage measure with subsequent robot intensity (compare table 2.5). Importantly, also in column (6), there is no significant relation of the ex-ante daily wage with subsequent changes in robot stock across panels, in contrast to the positive association of the AKM plant effect in table 2.6.

All in all, I conclude that for more homogeneous samples in terms of worker quality, plant size, and previous robot use, the wage measure can be a reasonable proxy for potential labor cost savings. However, for several intensive margin regressions this proxy cannot capture the firm wage premium effect that is linked more closely with economic theory.

These results for the average daily wage per employee as a proxy for potential labor cost savings can be discussed with respect to the existing empirical literature. In fact, Acemoglu et al. (2022) that identify a positive correlation of higher average wages with subsequent advanced technology adoption.[51] They interpret this as potential confirmation of the theoretical prediction that higher wages rise incentives for automation, or alternatively as a result of selection in line with Doms et al. (1997), where adopters

[50] Note that including the control for task composition does qualitatively not change results for the wage measure on the extensive margin. Due to the trade-off with sample size I do not include this variable for the intensive margin regressions.

[51] Note that the analysis in Acemoglu et al. (2022) is based on the full sample of U.S. firms, controlling for a firm's activity in manufacturing. Estimations are also based on a linear probability model where reported robot use between 2016 and 2018 is regressed on base years firm-level characteristics in 2015.

Table 2.8: Log Average Wage and Intensive Margin Robot Use

	(1)	(2)	(3)	(4)	(5)	(6)
	Annual Robot Stock					Δ Robot Stock
	2014	2015	2016	2017	2018	2014-2018
PANEL A: ALL ROBOT USING PLANTS						
Log Daily Wage	0.2457	0.3486**	0.2672	0.2739	0.1274	-0.0863
	(0.1744)	(0.1632)	(0.1694)	(0.1952)	(0.2661)	(0.3625)
N	218	241	267	287	325	325
PANEL B: ALL ROBOT USING PLANTS, EXCLUDING LARGEST 10%						
Log Daily Wage	0.3876**	0.4661***	0.4769**	0.4530**	0.2795	-0.0027
	(0.1489)	(0.1598)	(0.1650)	(0.1743)	(0.2311)	(0.0091)
N	156	168	187	201	228	228
PANEL C: INCUMBENT USERS, EXCLUDING LARGEST 10%						
Log Daily Wage	0.4511**	0.5627**	0.5709**	0.5577**	0.3948	0.0764
	(0.1959)	(0.2501)	(0.2207)	(0.2337)	(0.2554)	(0.4311)
N	194	194	194	194	194	194
	Annual Robot Intensity					
	2014	2015	2016	2017	2018	
PANEL D: ALL ROBOT USING PLANTS						
Log Daily Wage	0.5937	0.4932	0.4968	0.4806	0.3783	
	(0.5792)	(0.5225)	(0.4720)	(0.4409)	(0.4403)	
N	218	239	265	284	320	
Industry	yes	yes	yes	yes	yes	yes
Plant Size	yes	yes	yes	yes	yes	yes
Robot Intensity	yes	yes	yes	yes	yes	yes

Notes: i) Baseline sample in Panel A and D consists of all robot using plants. Panel B excludes from the 10% largest plants from the previous sample. Panel C keeps only incumbent users and then excludes the largest 10% of plants respectively. ii) Estimations in columns 1-5 are based on equation 2.9, where for Panels A-C, the dependent variable is the annual log number of robots per year for 2014 to 2018; in Panel D, it is the log number of robots per 1000 employees respectively. column 6 is based on equation 2.10, with the first difference in robot stock between 2014 and 2018 (in logs) as dependent variable. iii) Log Daily Wage is the average daily wage per plant in 2013 based on data from full-time employees in the IAB BHP data set. Plant size is the log number of employees in 2013. Robot intensity is the number of robots per 1000 employees in 2014. (iv) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes. *** p<0.01, ** p<0.05, * p<0.1 .

have ex-ante a higher skilled workforce, or as a result of reallocation of labor to other complementary tasks that pay higher mean wages (especially for incumbents).

At first glance, their finding stands in contrast to the extensive margin results discussed above, where the wage measure shows a negative association with the subsequent probability of adopting (additional) robots among German plants. Only for a selected sample of robot-using plants intensive margin regressions show a positive relation of log daily wage in 2013 with subsequent robot use. While for robot stock numbers, the coefficients of interest are positive and overall interpreted as weakly significant, for changes in robot stock or robot intensity, the relation is estimated to be ambiguous or non-significant.

However, there are some noteworthy differences between Acemoglu et al. (2022) and this paper's analysis in terms of sample characteristics and measurements of robot use and labor costs. Firstly, their sample is based on the full sample of U.S. firms in contrast to a selective sample of German manufacturing plants with at least 20 employees.[52] Secondly, they can only measure the use of robotics between 2016 and 2018 but not distinguish between new adopters and incumbent users, which neglects potentially relevant heterogeneity. Thirdly, they have to rely on average wages as a proxy for firm wage premia due to a lack of respective employer-employee data, while this paper can establish a closer link with economic theory by utilizing the AKM decomposition of average wages.

Nevertheless, in the U.S. average wages might be a more suitable proxy to test the model implications than for Germany. In fact, firm-specific premia are comparatively lower in U.S. manufacturing firms and have been declining (Bloom et al., 2018), while workers in Germany become more and more sorted by firm size and wage premiums of large firms have been stable to slightly rising (Lochner et al., 2020).

[52] Note that they investigate several advanced technologies that are also applied outside the manufacturing sector, while the focus on industrial robot use in this paper make a respective sample selection necessary.

2.5 Discussion

This paper contributes to the literature on wages and advanced technology adoption by testing two core assumptions in canonical models of automation, where increasing labor costs imply automation incentives for firms and first-time integration fixed costs are potential barriers to technology adoption. To guide my empirical analysis, I formulate a task-based production framework to model the profitability of advanced technology adoption conditional on relative effective costs of specialized capital and labor. It shows that theoretically, the role of labor costs is ambiguous depending on the differential replacability of workers across different tasks and the elasticity of substitution.

Respective model implications are tested using high-quality employer-employee data for German manufacturing plants, where plant-level robot use is linked with administrative worker-level data on wages and, importantly, AKM wage decomposition estimates, establishing a close link with economic theory. Thereby, robots are a relevant advanced technology that can perform an increasing amount of tasks and substitute employees to a much larger extent than previous automation technologies (Autor, 2015). At the same time, robots have high purchasing and integration costs that might diminish potential labor cost savings from task automation (Leigh et al., 2022). Consequently, the resulting data set allows for an analysis on a very granular level that is advantageous compared to previous empirical assessments.

My empirical results are based on cross-sectional estimations where I regress a dummy for robot stock increase between 2014 and 2018 on the ex-ante firm wage premium (estimated for the period 2007-2013), controlling for relevant plant level characteristics in 2013. Respective results suggest that larger potential labor cost savings in the form of firm-specific wage premia can partly explain subsequent robot adoption patterns. In fact, for the baseline sample, there is no significant relation between the ex-ante firm wage premium and robot stock increase. However, when new cage robot adopters with particularly high first-time technology integration costs are excluded, a significant positive relation appears for the remaining plants. This supports the assumption in the theoretical literature that high first-time adoption costs can mute potential gains from labor substitution in production. Additionally, I address in a subset of regressions the relation of the firm wage premium with subsequent intensive margin robot use, i.e. the number of robots (per 1000 employees) and growth in robot stock, and conclude that labor costs play a significant role for technology deepening among incumbent robot users.

In order to highlight the importance of the choice of measurement and to relate my results to previous empirical evidence, I run equivalent regressions with log average daily wage per plant as a measure for labor costs. I show that this wage measure is significantly negatively related to robot adoption on the extensive margin, which is according to the AKM wage decomposition driven by the worker-specific component (worker quality), while the firm-specific component is positively associated with robot stock increase. However, for more homogeneous samples in terms of workforce composition, previous advanced technology diffusion, and size, the wage measure is likely to become a better proxy for the firm wage premium, which captures a firm's incentive to automate tasks.

Finally, there are a few relevant caveats to consider. First, the discussed empirical results are based on a relatively small sample of German manufacturing plants that survived between 2007 and 2019. However, both robot adoption and firm wage premium are phenomena that predominantly exist in large manufacturing plants (Deng et al., 2023b; Lochner et al., 2023b), such that I expect the impact of the survival bias to be relatively low. However, secondly, this selection of larger plants into the sample entails an endogeneity issue, that can only be addressed to a certain extent in this paper. Thirdly, there is the issue of a potential omitted variable bias regarding managerial decisions, where robot adoption might be simply part of an expansion strategy regardless of its ex-ante firm wage premia. In fact, within an industry the frontier firms might simply adjust to the latest technology to stay at the frontier, a concern that has been raised in the literature on determinants of technology adoption and worker skill (Doms et al., 1997). Nevertheless, I argue that relatively higher labor costs might give firms an additional incentive to invest in advanced technologies, particularly in those that substitute labor in an increasing range of tasks. Note that employment in such firms does not necessarily have to decline with robot adoption for the labor cost saving channel to be valid. They might save future labor costs by hiring less, if they decide to integrate advanced technologies, such as robots.

Therefore, altogether, the presented results in this paper need to be interpreted as extensive descriptive evidence of robot adoption patterns in large, surviving, manufacturing plants that use the still scarce technology. Nevertheless, this analysis creates valuable new insights into the plant-level relationship between ex-ante firm-wage premia and robot adoption, that future research can build upon. With further micro-level data sets that capture a larger number of robot users over a longer time period, future research might be able to causally identify the micro-level relationship of labor costs and advanced technology adoption. Thereby, it can be advantageous to use wage decomposition estimates, as shown in this analysis. Further, variation within the group of robot users could be used to test the heterogeneity of the relation with respect to other determinants of robot adoption, such as institutional, organizational, and financial barriers.

From a policy perspective, it is relevant to understand the underlying firm-level decisions with respect to competition in input markets, e.g., in Germany with respect to high-skilled labor scarcity, as well as competition in output markets.

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Appendix

A2.1 Additional Tables

Table A2.1: Robustness of extensive margin results: alternative size measures

	Robot stock increase					
	(1)	(2)	(3)	(4)	(5)	(6)
Plant AKM	0.0207**	0.0233**	0.0196*	0.0214**	0.0285***	0.0217**
	(0.0094)	(0.0098)	(0.0103)	(0.0091)	(0.0091)	(0.0097)
Size 2010	0.0671***					
	(0.0138)					
Size 2011		0.0651***				
		(0.0152)				
Size 2012			0.0681***			
			(0.0158)			
Size 2010 (FT)				0.0644***		
				(0.0124)		
Size 2011 (FT)					0.0554***	
					(0.0119)	
Size 2012 (FT)						0.0636***
						(0.0138)
N	1481	1504	1519	1480	1503	1518
Industry	yes	yes	yes	yes	yes	yes
Avg. Worker AKM	yes	yes	yes	yes	yes	yes

Notes: i) Regressions are depicted for the baseline sample of manufacturing plants with at least 20 employees in the base year 2013, excluding first-time cage robot adopters. ii) Estimations are based on equation 2.8. The dependent variable is a dummy for robot stock increase that is equal to 1 if the number of robots in 2018 exceeds the number of robots in 2014. All regressions include the standardized firm wage premium per plant for the period 2007-2013, the average worker AKM effect per plant in 2013, and industry-level controls. iii) Columns vary in terms of plant size control. Columns 1 to 3 include the log number of employees in 2010, 2011, and 2012. Columns 4 to 6 include the log number of full-time (FT) employees, respectively. (iv) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes. *** p<0.01, ** p<0.05, * p<0.1 .

Table A2.2: Robustness of Intensive Margin Results on Robot Growth

	Δ Robot Stock								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Plant AKM (2007-2013)	0.3005**	0.2270*	0.2197**	0.2464*	0.2417*	0.2462*	0.2636*	0.2505**	0.2661**
	(0.1246)	(0.1281)	(0.1005)	(0.1265)	(0.1169)	(0.1233)	(0.1265)	(0.1097)	(0.1009)
Collective Agreement	-0.1561								
	(0.2002)								
Works Council		0.0993							
		(0.1324)							
Labor Scarcity			0.3723*						
			(0.1944)						
Foreign Ownership				0.0245					
				(0.3958)					
Competitive Pressure					0.0718				
					(0.1642)				
Export Status						0.1409			
						(0.2138)			
Technology Status							0.4526***		
							(0.1395)		
Organizational Changes								0.4346**	
								(0.1830)	
Above Median Growth									0.3492**
									(0.1350)
N	218	218	217	196	218	210	217	218	218
Avg. Worker AKM	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry	yes	yes	yes	yes	yes	yes	yes	yes	yes
Plant Size	yes	yes	yes	yes	yes	yes	yes	yes	yes
Robot Intensity 2014	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: i) The sample consists of manufacturing plants with at least 20 employees in base year 2013 that already used robots in 2014 (incumbents). Across columns observation numbers vary due to missings in the added control variables. ii) Estimations are based on equation 2.10. The dependent variable is in Panel the first difference in robot stock between 2014 and 2018 (IHS transformed). iii) Plant AKM is the standardized firm wage premium per plant for the period 2007-2013. Average worker quality is measured by the respective average worker AKM effect per plant in 2013. Plant size is controlled for with the log number of employees in 2013. Robot intensity is the number of robots per 1000 employees in 2014. (iv) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A2.3: Robustness of Intensive Margin Results on Robot Growth to Task Composition

	Δ Robot Stock		
	(1)	(2)	(3)
Plant AKM (2007-2013)	0.2211*	0.1957	0.1931*
	(0.1110)	(0.1132)	(0.0995)
Manual Tasks	-3.8656		
	(2.2748)		
Efficient Tasks		0.6126	
		(0.3591)	
Routine Tasks			2.0556**
			(0.7808)
N	246	246	246
Avg. Worker AKM	yes	yes	yes
Industry	yes	yes	yes
Plant Size	yes	yes	yes
Robot Intensity 2014	yes	yes	yes

Notes: i) The sample consists of manufacturing plants with at least 20 employees in base year 2013 that already used robots between 2014 and 2018. ii) Estimations are based on equation 2.10. The dependent variable is in Panel the first difference in robot stock between 2014 and 2018 (IHS transformed). iii) Plant AKM is the standardized firm wage premium per plant for the period 2007-2013. Average worker quality is measured by the respective average worker AKM effect per plant in 2013. Plant size is controlled for with the log number of employees in 2013. Robot intensity is the number of robots per 1000 employees in 2014. iv) From the QAC 2012 data set across columns, controls are added regarding occupation-based task composition per plants (in %), i.e., the share of common programmable routine manual tasks that can be performed by robots, the share of tasks with high-efficiency requirement, or the share of routine tasks. (v) Standard errors in parenthesis are clustered at WZ2008 2digit industry codes. *** p<0.01, ** p<0.05, * p<0.1 .

A2.2 Theoretical Appendix

Baseline setting

As in section 2.2, I firstly consider the profit function of a firm i that only produces output with input factor labor. Given firm i's demand I insert $p_i = \zeta^{\frac{1}{\eta}} y_i^{-\frac{1}{\eta}}$:

$$\begin{aligned} \pi_i(\ell_i) &= y_i\, p_i - w_i\, \ell_i \\ &= \zeta^{\frac{1}{\eta}}\, y_i^{1-\frac{1}{\eta}} - w_i\, \ell_i \\ &= \zeta^{\frac{1}{\eta}}\, A_i^{1-\frac{1}{\eta}} \ell_i^{1-\frac{1}{\eta}} - w_i\, \ell_i \end{aligned} \tag{2.11}$$

The respective first order condition, i.e. $\frac{\delta\, \pi_i(\ell_i)}{\delta\, \ell_i}$, gives:

$$w_i = \left(1 - \frac{1}{\eta}\right) \zeta^{\frac{1}{\eta}} A_i^{1-\frac{1}{\eta}} \ell_i^{-\frac{1}{\eta}} \tag{2.12}$$

Solving for optimal labor demand and plugging it back into the profit function, gives

$$\begin{aligned} \ell_i^* &= \left(1 - \frac{1}{\eta}\right)^{\eta} \zeta A_i^{\eta-1} w_i^{-\eta} \\ \pi_i(\ell_i^*) &= \zeta^{\frac{1}{\eta}} A_i^{1-\frac{1}{\eta}} \left[\left(1 - \frac{1}{\eta}\right)^{\eta} \zeta A_i^{\eta-1} w_i^{-\eta}\right]^{1-\frac{1}{\eta}} - w_i \left(1 - \frac{1}{\eta}\right)^{\eta} \zeta A_i^{\eta-1} w_i^{-\eta} \\ &= \zeta \left(1 - \frac{1}{\eta}\right)^{\eta-1} A_i^{\eta-1} w_i^{1-\eta} - \left(1 - \frac{1}{\eta}\right)^{\eta} A_i^{\eta-1} w_i^{1-\eta} \\ &= \zeta \frac{(\eta-1)^{\eta-1}}{\eta^{\eta-1}} \left(\frac{A_i}{w_i}\right)^{\eta-1} - \zeta \frac{(\eta-1)^{\eta}}{\eta^{\eta}} \left(\frac{A_i}{w_i}\right)^{\eta-1} \\ &= \zeta \frac{(\eta-1)^{\eta-1}}{\eta^{\eta}} \left(\frac{A_i}{w_i}\right)^{\eta-1} (\eta - (\eta-1)) \\ &= \zeta \frac{(\eta-1)^{\eta-1}}{\eta^{\eta}} \left(\frac{A_i}{w_i}\right)^{\eta-1} \end{aligned} \tag{2.13}$$

If a firm produces in addition to labor with specialized capital (robots), the profit function changes as described in equation 2.4 in the main text.

First-order conditions that solve for optimal input of robots (k_i^*) and labor (ℓ_i^*) lead to the following optimal operating profit function:

$$\pi_i(\ell_i^*, k_i^*) = \zeta \frac{(\eta-1)^{\eta-1}}{\eta^\eta} \left(\frac{A_i}{(\theta(r/\lambda)^{1-\sigma} + (1-\theta) w_i^{1-\sigma})^{\frac{1}{1-\sigma}}} \right)^{\eta-1} \tag{2.14}$$

Firm Wage Premium and Change in Profit

The change in profit following robot adoption is derived from equations 2.13 and 2.14 as follows:

$$\begin{aligned} \Delta\pi_i &\equiv \zeta \frac{(\eta-1)^{\eta-1}}{\eta^\eta} \left[\left(\frac{A_i}{(\theta(r/\lambda)^{1-\sigma} + (1-\theta) w_i^{1-\sigma})^{\frac{1}{1-\sigma}}} \right)^{\eta-1} - \left(\frac{A_i}{w_i} \right)^{\eta-1} \right] \\ &= \zeta \frac{(\eta-1)^{\eta-1}}{\eta^\eta} A_i^{\eta-1} \left[(\theta(r/\lambda)^{1-\sigma} + (1-\theta) w_i^{1-\sigma})^{\frac{1-\eta}{1-\sigma}} - w_i^{1-\eta} \right] \end{aligned} \tag{2.15}$$

To discuss how $\Delta\pi_i$ changes with w_i, I ignore the constant terms and derive the following equation:

$$\begin{aligned} \frac{\partial \Delta\pi_i}{\partial w_i} &= (1-\eta)(1-\theta) \left(\theta(r/\lambda)^{1-\sigma} + (1-\theta) w_i^{1-\sigma} \right)^{\frac{\sigma-\eta}{1-\sigma}} w_i^{-\sigma} - (1-\eta) w_i^{-\eta} \\ &\quad + \frac{1-\eta}{1-\sigma} \left(\theta(r/\lambda)^{1-\sigma} + (1-\theta) w_i^{1-\sigma} \right)^{\frac{\sigma-\eta}{1-\sigma}} \left((r/\lambda)^{1-\sigma} - w_i^{1-\sigma} \right) \frac{\partial \theta}{\partial w_i}, \end{aligned} \tag{2.16}$$

where the term in the second line represents the channel that a higher firm wage premium tends to raise the share of automatable tasks. It can be easily shown that this term is always positive. Thus, I focus on the terms in the first line:

$$\begin{aligned} &(1-\eta)(1-\theta) \left(\theta(r/\lambda)^{1-\sigma} + (1-\theta) w_i^{1-\sigma} \right)^{\frac{\sigma-\eta}{1-\sigma}} w_i^{-\sigma} - (1-\eta) w_i^{-\eta} \\ =&(\eta-1) w_i^{-\sigma} \underbrace{\left[w_i^{\sigma-\eta} - (1-\theta) \left(\theta(r/\lambda)^{1-\sigma} + (1-\theta) w_i^{1-\sigma} \right)^{\frac{\sigma-\eta}{1-\sigma}} \right]}_{\equiv \Delta c} \end{aligned} \tag{2.17}$$

Since $\eta > 1$, I discuss in the following three possible cases to sign the term Δc.

1. If $\sigma > \eta$ (elasticity of substitution between all tasks in production is sufficiently high), then

$$\begin{aligned} &\left[(1-\theta)^{\frac{\sigma-1}{\sigma-\eta}} - (1-\theta)\right] w_i^{1-\sigma} < 0 < \theta(r/\lambda)^{1-\sigma} \qquad (2.18)\\ \iff &\left[1-(1-\theta)^{\frac{1-\eta}{\sigma-\eta}}\right] w_i^{1-\sigma} < (1-\theta)^{\frac{1-\sigma}{\sigma-\eta}}\theta(r/\lambda)^{1-\sigma}\\ \iff &w_i^{1-\sigma} < (1-\theta)^{\frac{1-\sigma}{\sigma-\eta}}(\theta(r/\lambda)^{1-\sigma} + (1-\theta)w_i^{1-\sigma})\\ \iff &w_i^{\sigma-\eta} > (1-\theta)(\theta(r/\lambda)^{1-\sigma} + (1-\theta)w_i^{1-\sigma})^{\frac{\sigma-\eta}{1-\sigma}}, \end{aligned}$$

where the last line follows from $\sigma > \eta > 1$. Then, $\Delta c > 0$. Together with the discussion above, this results in $\frac{\delta \pi_i}{\delta w_i} > 0$ if $\sigma > \eta$.

2. If $\eta > \sigma > 1$ (elasticity of substitution between all tasks in production is relatively low) and $r/\lambda < w_i$ but it is sufficiently close to w_i, i.e., effective costs of robots are only slightly smaller than those for labor, then:

$$\begin{aligned} &\left[(1-\theta)^{\frac{\sigma-1}{\sigma-\eta}} - (1-\theta)\right] w_i^{1-\sigma} > \theta(r/\lambda)^{1-\sigma} \qquad (2.19)\\ \iff &\left[1-(1-\theta)^{\frac{1-\eta}{\sigma-\eta}}\right] w_i^{1-\sigma} < (1-\theta)^{\frac{1-\sigma}{\sigma-\eta}}\theta(r/\lambda)^{1-\sigma}\\ \iff &w_i^{1-\sigma} > (1-\theta)^{\frac{1-\sigma}{\sigma-\eta}}(\theta(r/\lambda)^{1-\sigma} + (1-\theta)w_i^{1-\sigma})\\ \iff &w_i^{\sigma-\eta} > (1-\theta)(\theta(r/\lambda)^{1-\sigma} + (1-\theta)w_i^{1-\sigma})^{\frac{\sigma-\eta}{1-\sigma}}, \end{aligned}$$

where the last line follows from $\eta > \sigma > 1$. Again, $\Delta c > 0$.

3. However, if $\eta > \sigma > 1$ but r/λ is sufficiently small, then

$$\begin{aligned} &\left[(1-\theta)^{\frac{\sigma-1}{\sigma-\eta}} - (1-\theta)\right] w_i^{1-\sigma} < \theta(r/\lambda)^{1-\sigma} \qquad (2.20)\\ \iff &\left[1-(1-\theta)^{\frac{1-\eta}{\sigma-\eta}}\right] w_i^{1-\sigma} < (1-\theta)^{\frac{1-\sigma}{\sigma-\eta}}\theta(r/\lambda)^{1-\sigma}\\ \iff &w_i^{1-\sigma} < (1-\theta)^{\frac{1-\sigma}{\sigma-\eta}}(\theta(r/\lambda)^{1-\sigma} + (1-\theta)w_i^{1-\sigma})\\ \iff &w_i^{\sigma-\eta} < (1-\theta)(\theta(r/\lambda)^{1-\sigma} + (1-\theta)w_i^{1-\sigma})^{\frac{\sigma-\eta}{1-\sigma}}, \end{aligned}$$

where the first line follows from $\sigma > 1$ and the last line follows from $\eta > \sigma > 1$. In this case, $\Delta c < 0$. This means how $\Delta\pi_i$ changes with w_i becomes ambiguous. Suppose the effect of w_i on θ is small. In that case, when the robot cost becomes sufficiently low due to the significant increase in the demand for workers performing complementary tasks, the incentives for robot adoption can be lower for high-w_i firms. Last, we can also consider $\sigma < 1$. The discussion of this case is essentially the same as that of the previous one.

Chapter 3

Minimum Wage, Workforce Composition, and Robot Adoption in Germany[1]

3.1 Introduction

With the rapid development of automation technologies in recent years, a growing body of literature studies the economics of automation and robotics in particular. While much of the research focuses on the consequences of robots, relatively less attention has been paid thus far to the causes of robot adoption. Theoretically, adopting robots, potentially bounded by technological and financial constraints, hinges on relative factor prices (Acemoglu and Restrepo, 2018a). The existing empirical evidence has documented at the industry and regional levels the role of relative factor prices in robot adoption decisions,[2] but causal evidence at the production-unit level remains very limited.

In this paper, we study the effect of the minimum wage on robot adoption at the plant level in Germany, where, in 2015, a statutory minimum wage was introduced for the first time. We use the minimum wage introduction as a quasi-natural experiment to study how an (exogenous) increase in labor cost affects robot adoption at the plant level. This setting provides an ideal testing ground for the relative-factor-price channel of robot adoption because, on the one hand, the economy-wide new legislation guaranteed a minimum hourly wage for most workers, marking a significant policy change,[3] and on the other hand, Germany, being a major player in robot innovation and production,

1 This chapter is joint work with Liuchun Deng and Jens Stegmaier.

2 See, e.g., causal evidence at the industry level based on the Japanese data (Adachi et al., 2024).

3 About 11% of German employees earned less than €8.50 before the minimum wage implementation (Bruttel, 2019).

has the highest robot density in Europe, thereby allowing us to investigate the effect of minimum wage at the forefront of automation technologies.

To guide our empirical analysis, we develop a simple task-based model of robot adoption as in Acemoglu and Restrepo (2018b). The effect of an increase in labor cost, induced by the minimum wage introduction, on robot adoption, is generally ambiguous and hinges on whether the minimum-wage-exposed workers are replaceable by robots. Our main empirical specification is a difference-in-difference setting that exploits whether and to what extent a plant is exposed to the 2015 minimum wage introduction. We find that the effect of the minimum wage on robot adoption, which is predicted to be ambiguous in a task-based framework, turns out to be positive in the context of Germany over the period of 2014–2018. The positive effect is statistically significant and economically sizable. Based on a binary measure of whether a plant has at least one worker with an hourly wage below €8.50 in 2013 (Butschek, 2022a), we find that being exposed to the minimum wage regulation is associated with an increase in the probability of robot adoption by 0.54-0.74 percentage points.[4]

Perhaps more importantly, we demonstrate using the worker-level data that the effect of the minimum wage on robot adoption hinges on the occupational composition of minimum-wage-exposed workers. According to our model, the minimum wage only raises the incentives for plants to adopt robots when it mainly bites replaceable workers. In our empirical setup, we construct the plant-level minimum wage exposure measures separately for workers in simple manual occupations, who are more replaceable by robots, and workers in other occupations. We find that the overall positive effect of the minimum wage on robot adoption stems solely from the plants with workers in simple manual occupations that are affected by the minimum wage, confirming the theoretical prediction.[5]

[4] Our sample's unconditional probability of robot adoption is 2.28%.

[5] This finding is also related to the empirical evidence of a negative impact of the minimum wage on the share of automatable employment as documented in Lordan and Neumark (2018).

This paper joins the literature on the determinants of advanced technology adoption, robot adoption in particular, at the micro level. Koch et al. (2021) document using the Spanish firm-level data that there is strong self-selection in robot adoption: firms with higher productivity ex ante are more likely to adopt robots. Zator (2019) uses the variation in labor scarcity at the plant and regional level to study its effect on the incentives of automation and digitalization. On average, labor scarcity is found to have a positive effect on technology investment. To our knowledge, Fan et al. (2021) is the first to study the impact of minimum wage on robot adoption and is therefore closely related to our paper. Using Chinese data, the authors study the effect of the introduction of minimum wage on firm-level robot imports. They adopt an instrumental variable approach based on the city-level variation in the minimum wage and find the effect to become positive in the more recent period. Freeman et al. (2024) adopt a similar research design to study the effect of minimum wage on firm-level robot imports in China and find the effect to be stronger among more routine-intensive firms.

Compared to the existing work, this paper makes two main contributions. First, we focus on a policy change that directly impacts the labor cost and exploit the variation in the exposure to policy change at the plant level, whereas the existing work on robot adoption and minimum wage mainly relies on city-level variation in minimum wage (Fan et al., 2021). The plant-level variation in minimum wage exposure facilitates a direct identification of the causal effect of the labor cost shock on automation incentives. Second, with the worker-level employment biographies, we can investigate the composition of the workers that are affected by the minimum wage. The resulting granular measures of minimum wage exposure enable us to confront the task-based theory with data: Not only the size but also the composition of the workforce that is affected by the minimum wage matters for robot adoption.

This paper also contributes to the vast literature on the firm-level effects of the minimum wage. Our baseline empirical setup follows closely Butschek (2022b), which studies the effect of the 2015 minimum wage introduction in Germany on employers' hiring standards. Bossler and Gerner (2020) adopt a similar empirical setup to study the employment effect with their treatment group based on survey measures of the minimum wage exposure.[6] From a substantive point of view, our work is related to Sorkin (2015) and Aaronson et al. (2018) that study the employment effect of the minimum wage in relation to the choice of technologies from the perspective of a putty-clay model. Aaronson and Phelan (2019) document a relative decline in cognitive routine occupations following the minimum wage and argue that cognitive routine tasks are more susceptible to technological substitution. In contrast with the relatively indirect evidence on the role of choice of technologies,[7] we provide direct evidence of how the minimum wage shapes the plants' incentives for robot adoption.

The rest of the paper is structured as follows. We introduce a task-based model of robot adoption and discuss the testable implications in the next section. We then describe our data, sample construction, and the econometric setting in Section 3. Our main empirical results will be presented with a battery of robustness checks in Section 4. We conclude in Section 5.

3.2 Model

To guide our empirical analysis, we introduce a simple model of robot adoption to discuss how the minimum wage affects firms' incentives for robot adoption. In our theoretical analysis, we demonstrate that the overall effect of minimum wage introduction on robot adoption is ambiguous but if the workers exposed to the minimum wage are *ex ante replaceable*, then the effect on robot adoption in the extensive margin becomes unambiguously positive. We also use the model to clarify under what condition the minimum wage affects the incentives of robot adoption in the intensive margin, especially for the firms that have already adopted robots.

[6] For an overview of the causal effects of the German minimum wage introduction, see Caliendo et al. (2019). For the effect of minimum wage on wage inequality in Germany, see Bossler and Schank (2023).

[7] Gustafson and Kotter (2023) document a negative association between the minimum wage and capital expenditures in the retail, restaurant, and entertainment industries. For the summary of this strand of work, see Clemens (2021).

We consider a simple task-based framework of robot adoption as in Acemoglu and Restrepo (2018b). In a given industry, firm i faces the iso-elastic demand $y_i = \gamma p_i^{-\eta}$, where $\eta > 1$ is the price elasticity, y_i and p_i are firm i's demand and price, and γ is a demand shifter. Firm i's production function follows the standard task-based specification

$$y_i = \phi_i \left(\int_0^1 s_i(j)^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}},$$

where ϕ_i is firm i's productivity, $s_i(j)$ is firm i's input of task $j \in [0, 1]$, and σ is the elasticity of substitution between different tasks.

Tasks can be completed by human labor or robots. We assume that for task j the productivity of robots relative to human labor is λ_j. For each task, human labor and robots are perfect substitutes. Firm i's input for task j is then given by

$$s_i(j) = \ell_i(j) + \lambda_j k_i(j),$$

where $\ell_i(j)$ and $k_i(j)$ are task-level input of labor and robots. We allow $\lambda_j = 0$ for some j, meaning some tasks are technologically non-automatable. To explore the differential impact of the minimum wage on workers performing different tasks, we allow the wage rate to be task-specific. In particular, workers performing task j, $\ell_i(j)$, are paid by w_j. Robots are assumed to have a flat rental rate of r. Our analysis focuses on a partial equilibrium setting so w_j and r are exogenously given.

For firms that have not adopted any robots, the first-time robot adoption has a fixed cost, F. Since in our empirical analysis, we also consider plants that have adopted robots prior to the minimum wage introduction, and we assume that those incumbent users do not face the fixed cost when they decide to adjust their robot stock. Since our focus is on the determinants of robot adoption, we abstract from the creation of new tasks following robot adoption as theoretically formulated in Acemoglu and Restrepo (2018b) and empirically investigated in Autor et al. (2024).

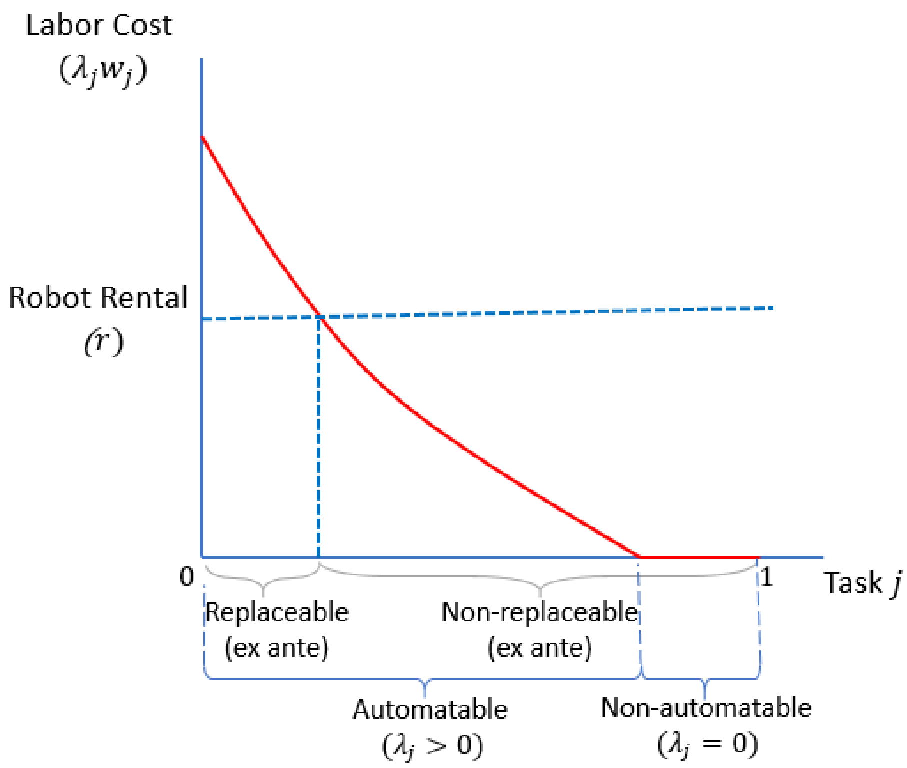


Figure 3.1: The Task-based Model

Since robots and human labor are perfect substitutes for the automatable tasks at the task level if firm i chooses to adopt robots, it will replace human labor with robots for tasks with $\lambda_j w_j > r$. Denote the set of tasks (and the workers performing those tasks) that will be performed by robots under robot adoption by $\mathcal{R} \equiv \{j \in [0, 1] : \lambda_j w_j > r\}$. We call those tasks in $\mathcal{R}$ *ex ante replaceable* because, in robot-using plants, workers performing those tasks are replaced by robots prior to the minimum wage introduction. We sort tasks such that $(\lambda_j w_j)$ decreases with j and illustrate the distribution of tasks in Figure 3.1.

When firm i decides whether to adopt robots for the first time, its trade-off is between the fixed cost of robot adoption and the cost savings in using robots to perform tasks in $\mathcal{R}$. If the cost saving exceeds F, firm i adopts robots.[8] When the minimum wage $\underline{w}$ is introduced, we have $w_j \geq \underline{w}$ for any j. The minimum wage affects the labor

[8] Since it is a static model of robot adoption, we abstract from the dynamics of robot investment and employment adjustment which are examined in a fully-fledged structural setting as in Humlum (2019).

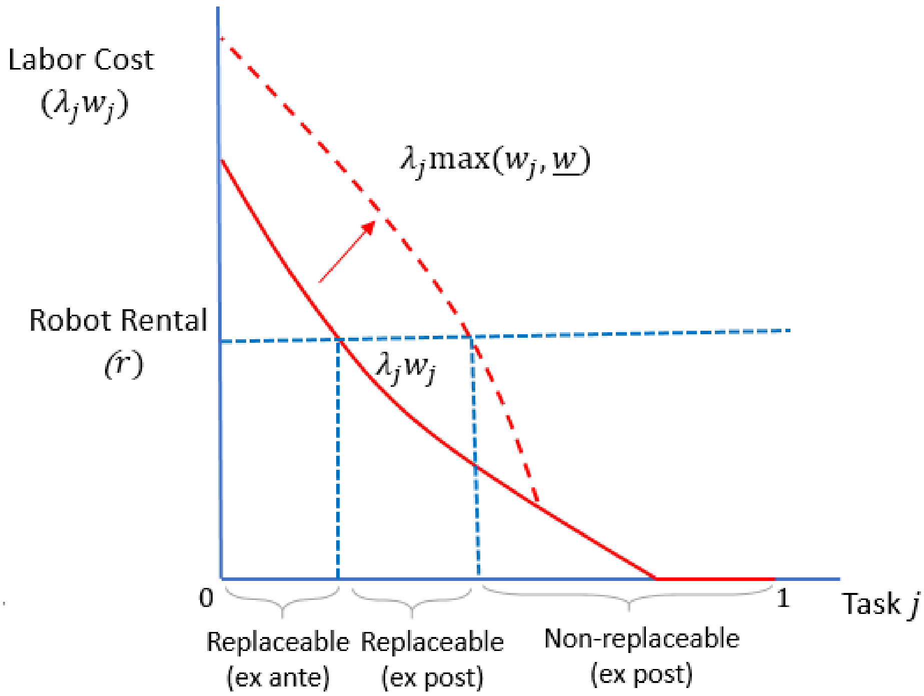


Figure 3.2: The Task-based Model with Minimum Wage

cost both before and after robot adoption. Our theoretical analysis thus centers around how the minimum wage affects the cost saving.

More tasks will be performed by robots under the minimum wage. We further partition the tasks that are not performed by robots prior to the minimum wage into two sets: the set of tasks that will only be performed by robots under the minimum wage is denoted by $\mathcal{R}' \equiv \{j \in [0,1] : \lambda_j w_j \leq r < \lambda_j \underline{w}\}$ and the set of tasks that continue to be performed by human labor under the minimum wage is denoted by $\mathcal{N} \equiv \{j \in [0,1] : \lambda_j \underline{w} \leq r \text{ and } \lambda_j w_j \leq r\}$. From now on, we simply refer to tasks in $\mathcal{R}'$ as *ex post replaceable* and tasks in $\mathcal{N}$ as *non-replaceable*. Figure 3.2 illustrates an example of how the minimum wage affects the productivity-adjusted wage curve.[9] To proceed, we discuss the effect of the minimum wage on the plant-level robot adoption in turn when the minimum wage only bites ex ante replaceable, ex post replaceable, and non-replaceable workers.

[9] It should be noted that in general, the minimum wage can create discontinuities in the productivity-adjusted wage curve because only a subset of workers are affected.

When the minimum wage only affects the ex ante replaceable workers, the pre-adoption labor cost rises. Because all those workers will be replaced by robots, the post-adoption cost of performing those tasks will not be affected by the minimum wage. In this case, the potential cost saving by robot adoption increases and therefore, non-robot users will have more incentives to adopt robots. For incumbent robot users, where the ex ante replaceable tasks have already been performed by robots, the minimum wage does not create an additional incentive to install more robots. The discussion yields our first proposition.

Proposition 1. *When the minimum wage only affects the ex an replaceable workers, it will have a positive effect on robot adoption in the extensive margin but no effect in the intensive margin.*

When the minimum wage only affects non-replaceable workers, both pre- and post-adoption production costs rise. The net change in cost saving depends on the elasticity of substitution between different tasks. Because the minimum wage raises the labor cost of non-replaceable tasks, a lower demand for non-replaceable workers translates into a lower demand for (ex ante and ex post) replaceable workers, when different tasks are complementary to each other. A lower demand for replaceable tasks will then reduce the cost savings of robots because robots only perform replaceable tasks. On the other hand, when the elasticity of substitution between tasks is high, a lower demand for non-replaceable tasks can raise the demand for tasks that robots perform and thus lead to more cost savings associated with robot adoption. For the incumbent users, the elasticity of substitution also affects their incentives for robot adoption in essentially the same way. This discussion is summarized in our next proposition.

Proposition 2. *When the minimum wage only affects the non-replaceable workers, it will have a negative effect on robot adoption in both the extensive and intensive margins when the tasks are relatively complementary to each other ($\sigma < \eta$) and the effect turns positive when the tasks are relatively substitutable by each other ($\sigma > \eta$).*

When the minimum wage only affects the ex post replaceable workers, again, both pre- and post-adoption production costs rise. The change in cost saving depends not only on the elasticity of substitution but also on the relative difference between $\lambda_j(\underline{w} - w_j)$ and $(r - \lambda_j w_j)$. The effect of the minimum wage on robot adoption is ambiguous in both the extensive and intensive margins. When the post-adoption increase in production cost (due to the minimum wage introduction), $\int_{j\in\mathcal{R}}(r - \lambda_j w_j)dj$, is sufficiently small, or the elasticity of substitution is relatively high ($\sigma > \eta$), the minimum wage will raise the incentives to install more robots for the incumbent users.

Proposition 3. *When the minimum wage only affects the ex post replaceable workers, its effect on robot adoption is ambiguous. When the minimum-wage-induced increase in post-adoption production cost is small, the effect on robot adoption is positive in the intensive margin.*

The following empirical implication follows immediately from the propositions above.[10]

Implication 1. *The effect of the minimum wage on robot adoption is generally ambiguous. When workers affected by the minimum wage are mainly ex ante replaceable, we expect a positive impact on robot adoption in the extensive margin.*

Before turning to the empirics, we briefly discuss the size-dependent channel of robot adoption. In our model, it is straightforward to show that there exists a threshold for productivity ϕ_i above which firm i chooses to adopt robots. Since firms with higher productivity are also larger in size, this result is consistent with the well-known empirical findings that larger plants are more likely to adopt robots. The following proposition suggests that such a scale effect in robot adoption is more prominent when robot prices are lower.

[10] This implication can be usefully compared with the theoretical findings in Fan et al. (2021). Whereas the effect of the minimum wage on robot adoption in the intensive margin is also proven to be ambiguous, their model, which abstracts from differential exposure to the minimum wage for workers performing different tasks, predicts an unambiguously positive effect on the extensive margin of robot adoption. More importantly, our model elaborates on how the minimum-wage effect relates to the notion of replaceability and thus provides a more explicit account of the relative factor price channel of robot adoption from the task perspective.

Proposition 4. *A drop in the fixed cost of adoption F or robot rental rate r raises the incentives of robot adoption in the extensive margin. A drop in r also has a positive effect on robot adoption in the intensive margin. Those effects are stronger for larger plants.*

During the sample period of our empirical analysis, there is a general decline in robot prices, so we expect that larger plants are likely to see a more significant increase in incentives for robot adoption: the scale effect in robot adoption is strengthened over time. Suppose the plant size is also correlated with the exposure to the minimum wage. In that case, this time-varying scale effect on robot adoption can potentially bias our empirical results of the impact of the minimum wage on robot adoption. We will address this concern in our econometric setup. Our next implication summarizes the discussion.

Implication 2. *The scale effect in robot adoption is likely to increase over time.*

3.3 Data and Empirical Approach

3.3.1 Data and Sample Construction

Our data on robot use at the plant level comes from the 2019 wave of the IAB Establishment Panel Survey, which is an annual survey of nearly 16,000 plants sampled from the population of German plants employing workers subject to social security contributions.[11] In the 2019 wave, plants are asked about whether they used robots from 2014 to 2018 and, if so, the number of robots in use in each year during that period. Based on the survey information, we construct a five-year panel for robot use at the plant level. A battery of consistency checks have been performed to ensure the high quality of the robot data.[12]

[11] The survey is nationally representative as a whole but also at the sector level, for firm-size classes, and across German federal states. For more information on the IAB Establishment Panel Survey, see Bechmann et al. (2019).

[12] For more details about the robot survey and the descriptive patterns, see Plümpe and Stegmaier (2023) and Deng et al. (2023).

We use the worker-level data to construct measures of minimum wage exposure. The worker-level data comes from the IAB Employment History (BeH), which contains all employment spells of workers subject to social security contributions.[13] The original BeH data is organized at the level of employment spells, we follow the standard procedure to select employment spells that cover the data of June 30 each year, and in the case of parallel spells, we keep the spell with the highest daily wage. We include only the employees subject to social security contributions without special characteristics (i.e., ordinary jobs and mini jobs). To compute the hourly wage for each worker, we follow Butschek (2022b) to divide the reported daily wage of full-time employees by 8 hours, assuming an 8-hour working day for full-time employees. Our results are robust to an alternative assumption of 7.5 hours per working day.

Based on the worker-level hourly wage, we construct several measures of minimum wage exposure at the plant level.[14] In particular, we exploit the variation in hourly wages prior to the minimum wage introduction in 2015. To avoid capturing potential anticipation effects in 2014, we choose the year 2013 as the baseline to construct the exposure measures.[15] Our first measure is a binary variable that indicates whether a plant has at least one employee (in 2013) with an hourly wage below the minimum wage threshold, €8.50 per hour.[16] Second, we construct two continuous measures to measure the extent of minimum wage exposure. The *bite* measure counts the number of workers in each plant with an hourly wage below €8.50. The *gap* measure computes the increase in a plant's total daily wage bill if it were to offer €8.50 for those whose hourly wages are below that threshold.[17]

13 The BeH is the main data source behind the publicly available SIAB data described in Frodermann et al. (2021).

14 Taking into account exemption clauses of the policy, we exclude employees that are apprentices, college student interns, and younger than 18 years old.

15 Our results are robust when we use the year 2012 instead for the construction.

16 Industries exempted from the minimum wage regulation in 2015 include meat, textile, clothing, and hairdressing. Plants in those industries are all tagged as non-minimum-wage exposed. We also include a robustness check to exclude all those industries from our analysis.

17 Formally, denote hourly wage for worker i in a given plant by w_i. The gap measure is given by $8 \times \sum_i \max\{8.5 - w_i, 0\}$. The multiplication by 8 is to convert hourly wage increases to daily wage increases.

Perhaps more importantly, we further construct the exposure measures separately for workers in simple manual occupations and for those in other occupations, with the workers in simple manual occupations identified through the widely used occupational categorization by Blossfeld (1987). Specifically, we construct the binary exposure measure for each occupation group based on whether a plant has at least one worker in that occupation group with an hourly wage below €8.50. We similarly construct the bite and gap measures separately for each occupation group at the plant level. The distinction between these occupational groups allows us to examine the heterogeneous effects of minimum wage exposure later.

To construct our estimation sample, we link the panel of robot data with the plant-level minimum wage exposure information. We exclude from our analysis very small plants with less than 10 employees in 2013 because robot adoption is rare among those small plants. The final sample contains 6,985 plants and covers a period of 5 years from 2014 to 2018. Among those 6,985 plants, 4,943 plants have at least one worker whose hourly wage is below €8.50 in 2013 and are thus classified as the baseline treatment group, whereas the control group consists of the remaining 2,252 plants.

Table 4.1 reports the basic summary statistics. In 2014, 4.6% (225/4,943) of the treatment group plants used robots, and the robot user share of this group rose to 7.2% (357/4,943) in 2018. In comparison, the corresponding figures of the control group plants are 2.0% (44/2,252) in 2014 and 3.1% (70/2,252). The share of plants that newly adopt robots over this period for the treatment group (2.6%) is thus more than twice that for the control group (1.1%). Regarding initial employment, plants in the treatment group are twice as large. Because it is well known that plant size plays an important role in robot adoption, we will discuss how we account for the initial employment differences in our econometric setup. By construction, the average wage in the treatment group was lower in 2013. The initial share of simple manual workers in those two groups is highly comparable.

Within the treatment group, the potential wage bill increase that would be necessary in 2013 to meet the hourly minimum wage of €8.50 for all employees (gap measure)

Table 3.1: Summary Statistics

Panel A: Main Variables (Treatment vs Control Group)		
	Treatment Group ($N = 4,943$)	Control Group ($N = 2,252$)
# Robot Users in 2014	225	44
# Robot Users in 2018	357	70
Average Employment	162.5	83.6
Average Wage	10.9	13.7
Share of Simple Manual Workers	11.6	11.9

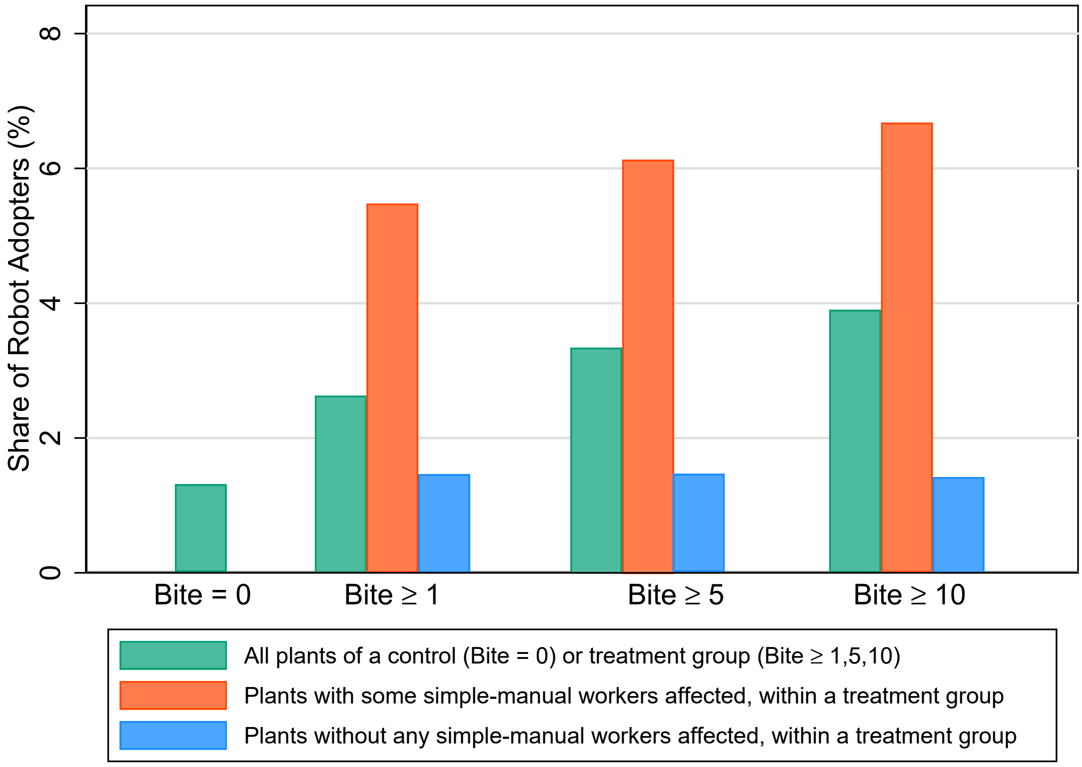
Panel B: Minimum Wage Exposure (Treatment Group Only)		
	Overall	Simple Manual
Average Gap Measure	194.2	39.6
Average Bite Measure	13.9	3.0

Notes: (i) This table reports the summary statistics. The definition of a treatment group is a plant with at least one worker whose hourly wage is below €8.50 in 2013. (ii) Panel A covers the main variables for both the treatment and control groups. The average employment, wage, and share of simple manual workers are based on the 2013 data. (iii) Panel B provides average minimum wage exposure measures (gap and bite) for the treatment group. We report the mean value for both the overall exposure and for only the simple manual workers. The calculations are based on the 2013 worker-level data.

is on average €194.20 per day, and the treated plants on average have 13.9 workers whose hourly wage is below €8.50 in 2013. If we only focus on the simple manual workers in the treated plants, this group's gap and bite measures account for slightly more than 20% of the plant-level total.

Figure 3.3 depicts the robot adoption rate, defined as the fraction of plants that newly adopted robots from 2014 to 2018 by minimum wage exposure (no exposure, at least 1/5/10 workers affected). As suggested by Table 4.1 before, the adoption rate is significantly higher among the treatment group plants, and the rate also increases with the treatment intensity. Interestingly, when we divide each treatment group by whether a plant has at least one simple-manual worker affected (orange vs. blue bars in the figure), we find that the positive association between minimum wage exposure and robot adoption is entirely driven by the plants with simple manual workers affected. Our econometric analysis thus attempts to formally establish those descriptive patterns in a more causal sense.

Figure 3.3: Robot Adoption and Minimum Wage Exposure



Notes: (i) This figure depicts the robot adoption rate (share of plants that newly adopted robots from 2014 to 2018) by minimum wage exposure. Each subsample excludes plants that already use robots in 2014. (ii) The green bar is the adoption rate for the control group ($Bite = 0$) and each treatment group with at least 1 (or 5, or 10) workers with an hourly wage below €8.5 in 2013. (iii) The orange and blue bars are the adoption rates for the subsample within each treatment group with or without workers in simple manual occupations exposed to the minimum wage regulation.

3.3.2 Empirical Approach

The starting point of our analysis is a standard difference-in-difference (DiD) setting. Following Butschek (2022b), we consider

$$y_{it} = \alpha_i + \delta_t + \beta(T_i \times Post_t) + \varepsilon_{it}, \tag{3.1}$$

where y_{it} is the outcome variable of interest for plant i in year t. We consider mainly two outcome variables, a dummy variable of robot use that equals one if a plant uses robots in a given year and zero otherwise (D_{it}^{robot}), capturing the extensive margin of robot adoption, and a continuous measure of the number of robots in use (N_{it}^{robot}), capturing the intensive margin of robot adoption. Ideally, we want to have N_{it}^{robot} in log level, but because of the zero values, we apply the inverse hyperbolic sine (IHS) transformation. To address the concerns about the IHS transformation (Bellemare and Wichman, 2020; Chen and Roth, 2024), we will consider several alternative specifications in the robustness checks. In Equation (3.1), α_i and δ_t are plant and calendar year fixed effects. T_i is a treatment dummy that equals one if plant i is exposed to the minimum wage regulation and zero otherwise. In our baseline setting, $T_i = 1$ if plant i has at least one worker whose hourly wage is below €8.50 in 2013.[18] $Post_t$ is the post-event dummy that equals one if year $t \geq 2015$. ε_{it} is the error term.

Our main identifying assumption is that in the absence of the minimum wage regulation, the treatment and control group plants would follow parallel trends in terms of robot adoption. However, from the summary statistics, we know that plants exposed to the minimum wage regulation are, on average, twice as large as the control group plants. Because robot adoption is strongly positively correlated with plant size, the ex ante size difference between the two groups poses a threat to the identification. To address this concern, we include an additional interaction term between employment (in 2013) and the *Post* dummy to partial out any *time-varying* effects of the plant size on robot adoption.

Further, we allow the treatment intensity to vary across plants by replacing T_i with the gap measure Gap_i in the equation above:

$$y_{it} = \alpha_i + \delta_t + \beta(Gap_i \times Post_t) + \varepsilon_{it}. \tag{3.2}$$

This regression is to tackle how the incentives to adopt robots change with the intensity of minimum wage exposure. In a very similar setting, we also replace T_i in Equation (3.1) with the bite measure $Bite_i$. To account for the skewness and to accommodate zeros in our analysis, we apply the IHS transformation to both continuous treatment measures. We will again address the concern pertaining to the IHS transformation later on.

18 We follow Butschek (2022b) and Cengiz et al. (2019) to confirm the validity of the treatment by studying the effect of the minimum wage on plant-level wage distribution. The results are reported in Appendix B.

A more substantive and perhaps theoretically more important departure from the baseline setting is to distinguish workers affected by the minimum wage who are more likely to be replaced by robots from other minimum-wage-exposed workers.

In particular, we consider

$$y_{it} = \alpha_i + \delta_t + \beta_1(T_i^{sm} \times Post_t) + \beta_2(T_i^{oth} \times Post_t) + \varepsilon_{it}, \tag{3.3}$$

where T_i^{sm} is a dummy variable that equals one if plant i has at least one worker in a simple manual occupation with an hourly wage below €8.50 in 2013 and T_i^{oth} is similarly defined as whether a plant has at least one worker in a non-simple-manual (other) occupation exposed to the minimum wage regulation. This specification captures the differential effect of minimum wage exposure by occupation group. Moreover, we consider

$$y_{it} = \alpha_i + \delta_t + \beta_1(Gap_i^{sm} \times Post_t) + \beta_1(Gap_i^{oth} \times Post_t) + \varepsilon_{it}, \tag{3.4}$$

where Gap^{sm} and Gap^{oth} are the IHS-transformed gap measures for workers in simple manual occupations and other occupations, respectively. By construction, $Gap_i^{sm} + Gap_i^{oth} = Gap_i$. Equivalently we consider a specification with $Bite^{sm}$ and $Bite^{oth}$ in the equation above.

Last, we investigate two slightly different samples throughout our empirical analysis. Because of the fixed cost of robot adoption for plants that have never used robots, the effect of the minimum wage on robot adoption in the extensive margin falls mainly on the non-users. Thus, when analyzing the binary outcome of whether robots are used (D^{robot}), we focus on the sample that consists of only plants that do not use any robots in 2014. When we turn to the analysis of the intensive margin (N^{robot}), we study both the sample without and with the incumbent users that already installed robots in 2014.[19]

[19] Among the incumbent users in 2014, only less than 1% of the plants stop using robots at some point in our sample.

3.4 Results

We present our empirical results in this section. We will demonstrate that the overall effect of the minimum wage on robot adoption, which is theoretically ambiguous, is positive in the German context. The positive effect is statistically significant and economically sizable. We then show that this positive effect stems from the minimum-wage-exposed workers in simple manual occupations who perform a larger share of routine tasks. Plants with only workers in other occupations exposed to the minimum wage regulation, however, do not see a significant increase in robot adoption. The heterogeneous effects underscore the role of occupation composition and are consistent with our theoretical prediction. We end this section with a comprehensive discussion about the sample selection, the construction of the minimum wage exposure measure, and how we address the issue of the IHS transformation.

3.4.1 The Overall Effect of the Minimum Wage

Table 3.2 presents the effect of the minimum wage on robot adoption based on the standard DiD setting as in Equation (3.1) with a binary treatment of whether a plant has at least one worker affected. Columns (1) and (2) report the effect of robot adoption in the extensive margin, based on the sample of plants that did not use robots in 2014. According to Column (1), the minimum wage exposure raises the probability of robot adoption by 0.74 percentage points since 2015. This is a significant increase in adoption probability as only less than 2% of German plants use robots in 2018 (Deng et al., 2023).

According to our model (Implication 3), when robot prices drop over time, the incentives for robot adoption increase more for larger plants. As a result, this time-varying scale effect, if not controlled for, can bias the effect of the minimum wage upward when larger plants are more likely to be affected by the minimum wage. Thus, we include the base-year plant size interacted with $Post_t$ in Column (2). The estimated effect of the minimum wage drops slightly to 0.54 percentage points but remains

Table 3.2: Minimum Wage and Robot Adoption: Binary Treatment

Dependent variable	Robot-use Dummy		Number of Robots			
Sample	w/o 2014 users		w/o 2014 users		w/ 2014 users	
	(1)	(2)	(3)	(4)	(5)	(6)
T×Post	0.0074***	0.0054**	0.0102***	0.0073***	0.0153***	0.0108***
	(0.0021)	(0.0021)	(0.0027)	(0.0026)	(0.0029)	(0.0029)
log(Emp)×Post		0.0065***		0.0093***		0.0142***
		(0.0012)		(0.0018)		(0.0020)
N	33580	33580	33573	33573	34918	34918

Notes: (i) This table reports the OLS estimates based on Equation (3.1). (ii) The dependent variable is the dummy of robot use in Columns (1) and (2) and the number of robots with IHS transformation in Columns (3)–(6). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1)–(4) and with the 2014 users for Columns (5) and (6). (iv) The treatment dummy $T = 1$ if at least one worker is affected by the minimum wage and the post dummy $Post = 1$ if year $t \geq 2015$. (v) Log(Emp) is the total number of workers in logs at the plant level in 2013. (vi) Both plant and calendar year fixed effects are included. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

statistically significant. Consistent with the model, according to the point estimate of log(Emp)×Post, we find the scale effect in adoption probability to increase significantly over time.

Columns (3)–(6) report the effect of the minimum wage on robot adoption in the intensive margin, based on the sample without and with the plants that already used robots in 2014. The effect is estimated to be positive across all columns. When we control for the time-varying scale effect, the estimated effect remains sizable with high statistical significance. Interestingly, when we compare the point estimates between the two samples, the estimated effect on the intensive margin becomes larger when the incumbent users are included.[20]

In Table 3.2, our binary treatment is based on whether at least one worker is affected by the minimum wage. We also consider alternative cutoffs of at least 3, 5, or 10 workers affected and report the results in Appendix Table A3.1. The estimated

[20] One way to rationalize this finding is that technology deepening by the incumbent users as a response to labor cost shocks is likely to be easier than robot adoption (for first-time users), which would require a reorganization of the production.

Table 3.3: Minimum Wage and Robot Adoption: Continuous Treatment

Dependent variable	Robot-use Dummy		Number of Robots			
Sample	w/o 2014 users		w/o 2014 users		w/ 2014 users	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: The Gap Measure (IHS)			
Gap×Post	0.0022***	0.0017***	0.0028***	0.0021***	0.0037***	0.0026***
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
log(Emp)×Post		0.0061***		0.0088***		0.0137***
		(0.0012)		(0.0018)		(0.0020)
			Panel B: The Bite Measure (IHS)			
N×Post	0.0041***	0.0032***	0.0051***	0.0038***	0.0065***	0.0044***
	(0.0009)	(0.0009)	(0.0012)	(0.0012)	(0.0013)	(0.0013)
log(Emp)×Post		0.0059***		0.0086***		0.0135***
		(0.0012)		(0.0018)		(0.0020)
N	33580	33580	33573	33573	34918	34918

Notes: (i) This table reports the OLS estimates based on Equation (3.2). (ii) The dependent variable is the dummy of robot use in Columns (1) and (2) and the number of robots with IHS transformation in Columns (3)–(6). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1)–(4) and with the 2014 users for Columns (5) and (6). (iv) In Panel A, the continuous treatment Gap captures the potential wage bill increase for a plant if it would have to pay at least the minimum wage in 2013. In Panel B, the continuous treatment is the number of affected workers. The post dummy $Post = 1$ if year $t \geq 2015$. Both *Gap* and N are IHS transformed. (v) Log(Emp) is the total number of workers in log at the plant level in 2013. (vi) Both plant and calendar year fixed effects are included. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

effect of minimum wage remains significantly positive. Its magnitude increases with the degree of exposure, in line with the descriptive patterns in Figure 3.3.[21]

To further explore the effect of the minimum wage exposure with varying intensity, we report the results based on Equation (3.2) with continuous treatment variables in Table 3.3. In Panel A, the results based on the gap measure suggest that the more a plant is exposed to the minimum wage shock, the more likely it is to adopt robots. The interquartile range for the gap measure among the treatment group plants is from €22 to €173 in our sample.

[21] Moreover, we also run a variant of Equation (3.1) by interacting the treatment dummy with a full set of yearly dummies. The point estimates of this dynamic setting, reported in Appendix Table A3.2, suggest the effect of the minimum wage on robot adoption to increase over time.

According to the point estimate in Column (2), controlling for the plant size, this interquartile range translates into a difference in adoption probability by 0.35 percentage points ($\ln(177/22) \times 0.0017 \approx 0.35$). It is worth noting that the time-varying scale effect remains significantly positive and is larger than the estimated treatment effect. Panel B presents the results based on the alternative bite measure. The point estimates, which are slightly larger in size, confirm the findings in Panel A. Both gap and bite measures are IHS transformed to accommodate for zero-valued observations. To ensure our results are not driven by the IHS transformation, we rerun regressions based on Equation (3.2) using both measures normalized by the plant-level employment in 2013 (without IHS transformation). The point estimates are reported in Appendix Table A3.3 and are consistent with the findings in Table 3.3.[22]

Another concern about the identification is that the low-wage plants may somehow have more incentives to adopt robots even in the absence of the minimum wage regulation. Since the plant fixed effect already absorbs the time-invariant differences in adoption incentives with wage level, this channel poses a threat to our identification only if the effect is time-variant. For instance, low-wage plants' additional incentives to adopt robots increase over time. To address this concern, we follow Butschek (2022b) and perform a placebo test by splitting the control group into plants with an average wage below the control-group median and those with an average wage above the median. We rerun our baseline specification by assigning the placebo treatment dummy equal to one for the plants with a below-median average wage. The estimated effects, reported in the first panel of Table 3.4, are statistically insignificant across all columns, suggesting the lack of a significant association between the average wage and robot adoption. Moreover, we run the placebo analysis based on a continuous treatment variable of the plant-level average wage in 2013 and report the results in Panel B. The insignificant

[22] Note in Appendix Table A3.3, when log(Emp)$\times$Post is controlled for, the point estimate is sometimes insignificant. This is because, unlike the gap and bite measure, the fraction of workers affected by the minimum wage is negatively correlated with the plant size. Therefore, the estimation of the normalized gap and bite measure can be biased by the scale effect in the opposite direction. Once the time-varying scale effect is controlled, the significantly positive estimates emerge again.

results alleviate the concern that the point estimates in Tables 3.2 and 3.3 simply capture the wage level effect.

3.4.2 The Role of Occupation Composition

Our task-based model predicts that the minimum wage is more likely to positively affect robot adoption when it mainly affects the ex ante replaceable workers (Implication 1). To test this theoretical implication, we split the workers exposed to the minimum wage into two groups by their occupation: workers in simple manual occupations who are more likely to be replaced by robots and workers in other occupations. As shown in

Table 3.4: Minimum Wage and Robot Adoption: Placebo Test

Dependent variable	Robot-use Dummy		Number of Robots			
Sample	w/o 2014 users		w/o 2014 users		w/ 2014 users	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Binary Placebo Treatment					
$T^{\text{Placebo}} \times$Post	0.0014	0.0036	0.0027	0.0055	0.0020	0.0059
	(0.0031)	(0.0031)	(0.0037)	(0.0040)	(0.0040)	(0.0042)
log(Emp)×Post		0.0078***		0.0097***		0.0123***
		(0.0025)		(0.0034)		(0.0034)
	Panel B: Continuous Placebo Treatment					
log(Wage)×Post	0.0025	0.0014	0.0019	0.0006	0.0045	0.0022
	(0.0035)	(0.0034)	(0.0039)	(0.0037)	(0.0040)	(0.0038)
log(Emp)×Post		0.0075***		0.0093***		0.0118***
		(0.0025)		(0.0033)		(0.0033)
N	9985	9985	9981	9981	10201	10201

Notes: (i) This table reports the placebo test results of Equation (3.1). (ii) The dependent variable is the dummy of robot use in Columns (1) and (2) and the number of robots with IHS transformation in Columns (3)–(6). (iii) The regression sample consists of the plants that were not affected by the minimum wage in 2014, without the incumbent 2014 robot users for Columns (1)–(4) and with the 2014 users for Columns (5) and (6). (iv) In Panel A, the treatment dummy $T = 1$ if a plant's average wage is below the median within the regression sample and the post dummy $Post = 1$ if year $t \geq 2015$. In panel B, the continuous placement treatment is the plant-level average wage (in log) in 2013. (v) Log(Emp) is the total number of workers in log at the plant level in 2013. (vi) Both plant and calendar year fixed effects are included. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.1, slightly more than one-fifth of the workers exposed to the minimum wage are in simple manual occupations.

Table 3.5: The Role of Occupation Composition: Binary Treatment

Dependent variable	Robot-use Dummy		Number of Robots			
Sample	w/o 2014 users		w/o 2014 users		w/ 2014 users	
	(1)	(2)	(3)	(4)	(5)	(6)
$T^{sm} \times$ Post	0.0229***	0.0212***	0.0281***	0.0256***	0.0431***	0.0386***
	(0.0042)	(0.0041)	(0.0054)	(0.0053)	(0.0058)	(0.0055)
$T^{oth} \times$ Post	0.0011	-0.0011	0.0029	-0.0002	0.0030	-0.0016
	(0.0020)	(0.0021)	(0.0026)	(0.0026)	(0.0028)	(0.0029)
log(Emp)×Post		0.0066***		0.0095***		0.0142***
		(0.0012)		(0.0018)		(0.0020)
N	33580	33580	33573	33573	34918	34918

Notes: (i) This table reports the OLS estimates based on Equation (3.3). (ii) The dependent variable is the dummy of robot use in Columns (1) and (2) and the number of robots with IHS transformation in Columns (3)–(6). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1)–(4) and with the 2014 users for Columns (5) and (6). (iv) The binary treatment T^{sm} is based on whether a plant has at least one worker in a simple manual occupation that is affected by the minimum wage and T^{oth} is based on whether a plant has at least one worker in a non-simple-manual occupation that is affected by the minimum wage. The post dummy $Post = 1$ if year $t \geq 2015$. (v) Log(Emp) is the total number of workers in log at the plant level in 2013. (vi) Both plant and calendar year fixed effects are included. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.5 presents the estimation results of Equation (3.3). Consistent with our model, when a plant has simple manual workers affected by the minimum wage, it experiences an increase in adoption probability. The effect, captured by the point estimate of $T^{sm} \times$ Post, is statistically significant across all specifications. According to Column (2), the exposure of simple manual workers to the minimum wage raises adoption probability by 2.14 percentage points. The estimated effect is quite sizable, about four times the estimated effect in our baseline setting (Column (2), Table 3.2), where we pool different types of minimum-wage-exposed plants together in a single treatment group. In contrast, according to the point estimate of $T^{oth} \times$Post, the exposure of other workers to the minimum wage has virtually no association with robot adoption.

Table 3.6 reports the estimation results of Equation (3.4). Panel A shows that the positive effect of the gap measure as in Table 3.3 stems entirely from the minimum-wage-exposed workers in simple manual occupations.

Table 3.6: The Role of Occupation Composition: Continuous Treatment

Dependent variable	Robot-use Dummy		Number of Robots			
Sample	w/o 2014 users		w/o 2014 users		w/ 2014 users	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: The Gap Measure (IHS): Simple Manual vs Other					
$\text{Gap}^{\text{sm}}\times$Post	0.0057***	0.0058***	0.0067***	0.0068***	0.0099***	0.0098***
	(0.0010)	(0.0010)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
$\text{Gap}^{\text{oth}}\times$Post	0.0005	-0.0001	0.0008	-0.0000	0.0003	-0.0010
	(0.0004)	(0.0004)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
log(Emp)×Post		0.0065***		0.0093***		0.0143***
		(0.0012)		(0.0018)		(0.0020)
N	33580	33580	33573	33573	34918	34918
	Panel B: The Bite Measure (IHS): Simple Manual vs Other					
$\text{N}^{\text{sm}}\times$Post	0.0111***	0.0112***	0.0130***	0.0131***	0.0183***	0.0182***
	(0.0021)	(0.0021)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
$\text{N}^{\text{oth}}\times$Post	0.0010	-0.0002	0.0014	-0.0003	0.0002	-0.0023*
	(0.0008)	(0.0009)	(0.0012)	(0.0012)	(0.0013)	(0.0014)
log(Emp)×Post		0.0064***		0.0093***		0.0144***
		(0.0012)		(0.0018)		(0.0020)
N	33580	33580	33573	33573	34918	34918
	Panel C: The Gap Measure (IHS): Replaceable vs Non-replaceable					
$\text{Gap}^{\text{repl}}\times$Post	0.0107***	0.0115***	0.0118***	0.0129***	0.0171***	0.0186***
	(0.0021)	(0.0022)	(0.0027)	(0.0027)	(0.0029)	(0.0029)
$\text{Gap}^{\text{non-repl}}\times$Post	-0.0053***	-0.0064***	-0.0056***	-0.0071***	-0.0084***	-0.0107***
	(0.0013)	(0.0013)	(0.0016)	(0.0017)	(0.0017)	(0.0018)
log(Emp)×Post		0.0063***		0.0088***		0.0138***
		(0.0012)		(0.0017)		(0.0019)
N	33485	33485	33478	33478	34823	34823

Notes: (i) This table reports the OLS estimates based on Equation (3.4). (ii) The dependent variable is the dummy of robot use in Columns (1) and (2) and the number of robots with IHS transformation in Columns (3)–(6). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1)–(4) and with the 2014 users for Columns (5) and (6). (iv) The continuous treatment is the gap measure (IHS transformed) in Panel A and the number of workers affected (IHS transformed) in Panel B, separately constructed for the simple manual occupations and for other occupations. In panel C, the Gap measure is decomposed into the replaceable and non-replaceable components through the occupation-level share of replaceable tasks matched with worker-level Gap measures. The post dummy $Post = 1$ if year $t \geq 2015$. (v) Log(Emp) is the total number of workers in log at the plant level in 2013. (vi) Both plant and calendar year fixed effects are included. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

According to Column (2), the magnitude of the estimated effect of Gap^{sm} is comparable to the (time-varying) scale effect (log(Emp)). A similar pattern carries over to the bite measure, as reported in Panel B: The treatment intensity has a positive association with robot adoption only for simple manual workers.

Admittedly, decomposing the workforce into simple manual and other occupations may not fully capture the underlying rich heterogeneity in replaceability across occupations. We, therefore, consider an alternative decomposition of the gap measure based directly on the occupation-level task information. Using the 2012 wave of the German Qualification and Career Survey (QAC), we compute the share of replaceable tasks among all tasks performed by each occupation.[23] We can compute at the plant level replaceable daily wage gap measure as $\text{Gap}^{\text{repl}} = 8 \times \sum_i (\max\{8.5 - w_i, 0\} \times \mathit{Repl}_i)$, where w_i is the hourly wage rate in 2013 for worker i in a given plant (multiplied by 8 to obtain the daily wage) and Repl_i is the share of replaceable tasks for worker i's occupation. Similarly, we can compute the non-replaceable gap measure as $\text{Gap}^{\text{non-repl}} = 8 \times \sum_i(\max\{8.5 - w_i, 0\} \times (1 - \mathit{Repl}_i))$. By construction, $\text{Gap} = \text{Gap}^{\text{repl}} + \text{Gap}^{\text{non-repl}}$. Panel C in Table 3.6 reports the estimation results of Equation (3.4) through this alternative decomposition. The replaceable gap measure is strongly positively associated with robot adoption, whereas the non-replaceable gap measure is strongly negatively associated. The results demonstrate that the underlying occupation replaceability drives the heterogeneous effect of minimum wage.

Even though we know from Table 4.1 that there is no discernible difference in the share of simple manual workers between the treatment and control groups, such a difference can arise when we compare treated plants in terms of intensity of minimum wage exposure, i.e., with high and low Gap^{sm}. Plants with relatively high Gap^{sm} tend to have a larger number of workers in simple manual occupations. The difference in

[23] The QAC data provides worker-level information about what tasks are performed in the workplace. We classify (i) manufacturing and producing goods and commodities, (ii) monitoring and control of machines, plants, and technical processes, and (iii) transporting, storing, and shipping as replaceable tasks (our regression results are robust if we also include cleaning, removing waste, and recycling as replaceable tasks). We compute the fraction of replaceable tasks among all tasks reported by each worker in the survey and then take the average to obtain replaceability at the 3-digit (KldB2010) occupation level.

occupation composition between different treatment sub-groups raises concern if the incentives to adopt robots increase over time for plants with a larger share of replaceable workers (for example, due to declining robot prices). In Appendix Table A3.4, we address this concern by including an interaction term between the base-year share of simple-manual workers (or plant-level replaceability) and *Post*. The point estimates are indeed smaller but remain statistically significant and economically sizable.

Thus, the results in Tables 3.5 and 3.6 underscore our theoretical prediction that the incentives for robot adoption rise significantly with labor costs if the minimum wage bites the more replaceable workers.

3.4.3 Discussions

To confirm the robustness of our results, we perform a battery of checks with respect to sample selection, measurement of plant-level minimum wage exposure, and the IHS transformation of intensive margin variables.

3.4.3.1 Sample Selection

To rule out the concern that specific sample characteristics are driving our results, we run robustness checks by excluding the most and least most robot-intensive industries and also by excluding control group plants with high average wages or relatively few employees.

The automobile industry is by far the most robot-intensive industry (Deng et al., 2023). To ensure our results are not just driven by robot adoption in this industry, we exclude the automobile industry and rerun all our main specifications. The results concerning the gap measure (specification (3.2)) and its decomposition by occupation (specification (3.4)) are reported in Panel A of Appendix Table A3.5.[24] We control for the time-varying scale effect for all columns, and in each column, we report point estimates for the two separate regressions. According to Panel A, our main results are essentially unchanged when the automobile industry is excluded from the analysis.

[24] We only report the results for gap measures to save space, but a fuller set of results concerning the binary treatment and the bite measures are available upon request.

In our baseline estimation, the sample includes non-manufacturing industries that use very few robots, so in Panel B, we only include the manufacturing industries and a selection of robot-intensive non-manufacturing sectors (agriculture, building and installation, wholesale and retail trade, and human health). The overall effect of minimum wage becomes insignificant for some specifications, but the estimates for Gap^{sm} are qualitatively unchanged across specifications.

Next, the control group contains plants with very high average wages, and those high-wage plants may differ greatly from the treatment group plants. We thus exclude control group plants whose initial wage in 2013 is above the control group median. Panel C suggests that those high-wage control group plants do not drive our findings. To further address the concern that our control group plants are, on average, smaller than the treatment group plants in terms of initial employment and, therefore, can contain disproportionately more small plants, we raise the minimum plant size (as of 2013) in our sample from 10 to 50 employees. This causes a significant drop in the sample size, but the estimation results, as reported in Panel D, are robust.[25]

3.4.3.2 Hourly Wage and Minimum Wage Exposure

We further perform robustness tests regarding our measure for plant-level treatment exposure in the worker-level data. For our analysis, the hourly wage is calculated for full-time workers with the assumption of 8 working hours per day in 2013. Firstly, we adopt here an alternative assumption of 7.5 hours per day to compute the hourly wage and reconstruct all our minimum wage exposure measures. The main results are robust and reported in Panel A of the Appendix Table A3.6. Secondly, we use the worker-level data from 2012 instead of 2013 to construct the minimum wage exposure measures to alleviate further the concern about the anticipation of the policy change. The estimation results are reported in Panel B. Third, the original worker-level data contains workers with implausibly low hourly wages far below €8.5. In our baseline

[25] Our main results are also robust when we exclude (i) plants in industries exempt from the minimum wage regulation, (ii) plants with less than 20 employees in 2013, or (iii) the control group plants whose employment pre-trend (employment growth between 2011 and 2013) is below the control group median.

setting, we exclude all workers with hourly wages in 2013 below €2.5 (in line with the wage bins created for the validity of the treatment test explained in Appendix B). We consider two alternatives: exclude workers with hourly wages below €4 and keep all workers with positive hourly wages. The results are reported in Panels C and D. Our main findings are robust to all those alternative minimum wage exposure constructions.

3.4.3.3 IHS Transformation

To accommodate zero-valued observations, we apply the IHS transformation to both the dependent variable (number of robots) and the explanatory variables (gap and bite measures). However, the recent econometrics literature has raised methodological concerns about the IHS transformation (Bellemare and Wichman, 2020; Chen and Roth, 2024). We have shown in Appendix Table A3.3 that our results for the gap and bite measures are qualitatively similar when we normalize those measures by the plant-level employment without taking any IHS transformation. Following the recommendation in Chen and Roth (2024), we measure the number of robots in percentile.

Appendix Table A3.7 reports the results for the gap measures with the IHS transformation and also in percentile. The main findings carry over. Last, we focus on the plants that already use robots in 2014, for which we can simply take the log of the number of robots. The sample of incumbent users is considerably smaller ($N = 1339$). According to Appendix Table A3.8, despite the limited sample size, the results based on the binary treatment measures suggest that the minimum wage raises the incentives for robot adoption in the intensive margin and this effect remains more pronounced among the plants with simple manual workers affected. The results based on the gap measures lose statistical significance but are still in line with our main findings in terms of the sign of the point estimates.

3.5 Conclusion

In this paper, we exploit the German minimum wage introduction in 2015 to document the positive effect of the minimum wage on robot adoption at the plant level. In line with the theoretical prediction, our empirical analysis demonstrates that the occupation composition of workers exposed to the minimum wage plays an important role in mediating the effect of a labor cost shock on automation. The minimum wage raises the incentives for plants to adopt robots when it mainly bites the workers in more replaceable, simple manual occupations.

Several questions remain open. First, it is natural to wonder how our findings on robot adoption can be extended to more general automation technologies (Aghion et al., 2020). It is both theoretically important and empirically interesting to understand the interplay between labor cost, the nature of different automation technologies, and occupation composition. Second, because the theoretical prediction of the minimum wage on robot adoption is generally ambiguous, empirical analysis based on the microdata in other industrialized economies would help us better understand whether and how the effect of the minimum wage on robot adoption depends on labor market institutions. Last, since the minimum wage introduction in Germany is also documented to generate the economy-wide aggregate impact, it would help inform the policymakers by evaluating its impact on the adoption of automation technologies through the lens of a fully-fledged general equilibrium model.

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Appendix

A3.1 Proofs

Proof of Proposition 1: When the minimum wage only affects the ex ante replaceable workers, it raises the labor cost of production prior to robot adoption, with the production cost unchanged after robot adoption. Because there is a fixed cost of first-time robot adoption, plants will have more incentives to adopt robots in this case.

However, for plants that have already adopted robots, the minimum wage only affects the workers who are already replaced by robot users, so the minimum wage does not have any effect on the incumbent users.

Proof of Proposition 2: When the minimum wage only affects non-replaceable workers, it raises the cost of production both before and after robot adoption. The profit prior to robot adoption is given by

$$\pi_i = \gamma \frac{(\eta-1)^{\eta-1}}{\eta^\eta} \left(\frac{\phi_i}{c}\right)^{\eta-1},$$

where $c = \left[\int_0^1 w_j^{1-\sigma} dj\right]^{\frac{1}{1-\sigma}}$ before the minimum wage introduction and $c = \left[\int_0^1 w_j^{1-\sigma} dj + \Delta w\right]^{\frac{1}{1-\sigma}}$ under the minimum wage, with $\Delta w \equiv \int_{\mathcal{N}} (\underline{w}^{1-\sigma} - w_j^{1-\sigma}) dj$. We note that $\Delta w < 0$ for $\sigma > 1$ and $\Delta w > 0$ for $\sigma < 1$. Similarly, the profit after robot adoption is given by

$$\pi_i' = \gamma \frac{(\eta-1)^{\eta-1}}{\eta^\eta} \left(\frac{\phi_i}{c'}\right)^{\eta-1},$$

where $c' = \left[\int_{j\notin\mathcal{R}} w_j^{1-\sigma} dj + \int_{\mathcal{R}} (r/\lambda_j)^{1-\sigma} dj\right]^{\frac{1}{1-\sigma}}$ before the minimum wage introduction and $c' = \left[\int_{j\notin\mathcal{R}} w_j^{1-\sigma} dj + \int_{\mathcal{R}} (r/\lambda_j)^{1-\sigma} dj + \Delta w\right]^{\frac{1}{1-\sigma}}$ under the minimum wage. Thus, under the minimum wage, the change in operating profit due to robot adoption is given by

$$\pi_i' - \pi_i = \gamma \frac{(\eta-1)^{\eta-1}}{\eta^\eta} \phi_i^{\eta-1} \left(c'^{1-\eta} - c^{1-\eta}\right),$$

which is a function of Δw.

We have:

$$\frac{\partial \left(c'^{1-\eta} - c^{1-\eta}\right)}{\partial \Delta w} = \frac{1-\eta}{1-\sigma} \left(\left[\int_{j\notin\mathcal{R}} w_j^{1-\sigma} dj + \int_{\mathcal{R}} (r/\lambda_j)^{1-\sigma} dj + \Delta w\right]^{\frac{\sigma-\eta}{1-\sigma}} - \left[\int_0^1 w_j^{1-\sigma} dj + \Delta w\right]^{\frac{\sigma-\eta}{1-\sigma}} \right).$$

For $\eta > 1 > \sigma$, we have $\frac{1-\eta}{1-\sigma} < 0$, $\frac{\sigma-\eta}{1-\sigma} < 0$, and $c'^{1-\sigma} < c^{1-\sigma}$, so $\frac{\partial(c'^{1-\eta} - c^{1-\eta})}{\partial \Delta w} < 0$. Since $\Delta w > 0$ for $\sigma < 1$, the introduction of the minimum wage lowers the operating profit differential, $\pi_i' - \pi_i$. For $\eta > \sigma > 1$, we have $\frac{1-\eta}{1-\sigma} > 0$, $\frac{\sigma-\eta}{1-\sigma} > 0$, and $c'^{1-\sigma} > c^{1-\sigma}$, so

$\frac{\partial\left(c'^{1-\eta}-c^{1-\eta}\right)}{\partial \Delta w} > 0$. Since $\Delta w < 0$ for $\sigma > 1$, the introduction of the minimum wage again lowers the operating profit differential.

For $\sigma > \eta > 1$, however, we have $\frac{1-\eta}{1-\sigma} > 0$, $\frac{\sigma-\eta}{1-\sigma} < 0$, and $c'^{1-\sigma} > c^{1-\sigma}$, so $\frac{\partial\left(c'^{1-\eta}-c^{1-\eta}\right)}{\partial \Delta w} < 0$, which implies that the minimum wage raises the operating profit differential. Thus, we have shown that minimum wage lowers the incentives for first-time robot adoption when $\sigma < \eta$ and raises the incentives when $\sigma > \eta$.

We now turn to the incumbent users. For plants that have already adopted robots, their robot use is given by

$$k_i = \phi_i^{\eta-1} c'^{\sigma-\eta} \gamma \left(1 - \frac{1}{\eta}\right)^{\eta} \int_{\mathcal{R}} \left(\frac{r}{\lambda_j}\right)^{-\sigma} dj, \tag{3.5}$$

where only c' is affected by the minimum wage. Since the minimum wage increases c', the effect on k_i hinges on $(\sigma - \eta)$. When $\sigma > \eta$, an increase in c' leads to an increase in k_i, whereas when $\sigma < \eta$, an increase in c' lowers k_i. In sum, the effect on the intensive margin follows that on the extensive margin. Thus, we have obtained the desired conclusion.

Proof of Proposition 3: The argument follows the proofs of Propositions 1 and 2.

Proof of Proposition 4: It is straightforward to show that a drop in the fixed cost of robot adoption F or the rental rate of robots r raises the incentives for first-time robot adoption. Further, from Equation (3.5), we know that robot use decreases with r, so a drop in the rental rate also increases robot adoption on the intensive margin. Since profit and robot use increase with the productivity term ϕ_i, the effects of a drop in F or r on robot adoption are stronger for plants with higher productivity (or, equivalently, for larger plants in this model).

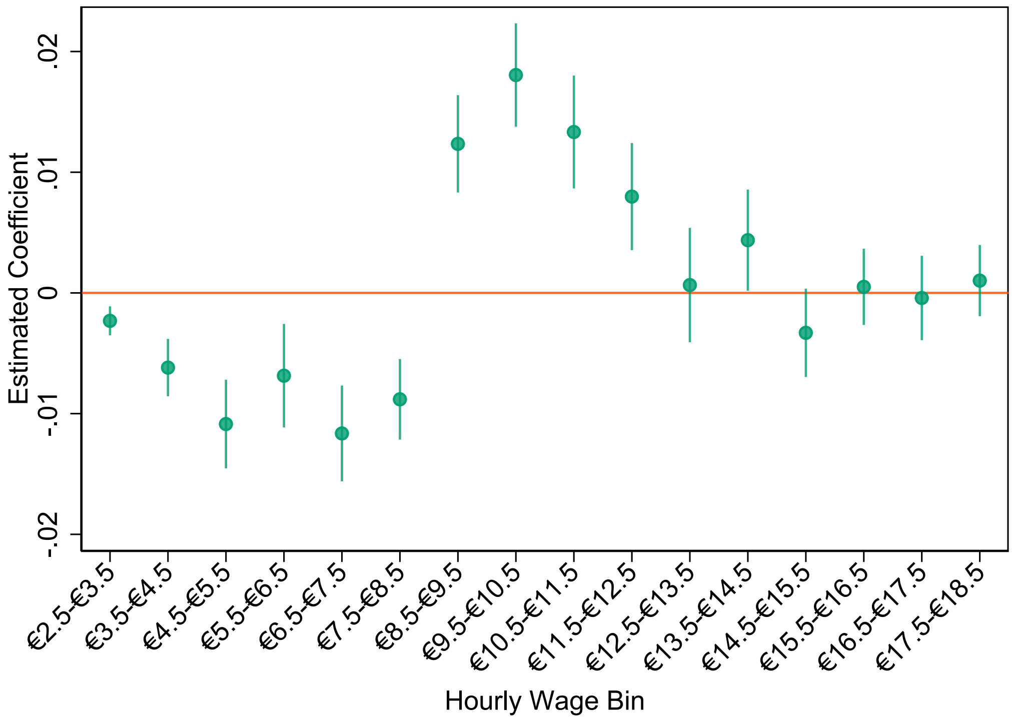
A3.2 Validity of Treatment

To establish the validity of the minimum wage exposure as a treatment, we follow Butschek (2022b) to run the following regression

$$y_{ijt} = \alpha_{ij} + \delta_{jt} + \sum_{k=-6}^{9} \beta_k (E_{ij}^k \times Post_t) + \varepsilon_{ijt}, \tag{3.6}$$

where y_{ijt} is the share of workers in plant i whose hourly wage is in wage bin j in year t. Wage bin j is hourly wage between $(8.5 - j)$ and $(9.5 - j)$ Euros. α_{ij} and δ_{jt} are wage-bin×plant and wage-bin×year fixed effects. E_{ij}^k is a dummy variable that equals one if plant i is treated and $j = k$. We consider in total 16 wage bins centering around the minimum wage €8.5. $Post_t$ is defined analogously as in our baseline setting and ϵ_{ijt} is an error term.

Figure A3.1: Effects of Minimum Wage Regulation on Hourly Wage



Notes: (i) This figure depicts the point estimates of β_k specified in Equation (3.6). (ii) The share of workers in each wage bin is computed based on the full-time workers. (iii) We restrict the time window to 2013-2016 so that the results are not affected by the subsequent increase in the minimum wage (from €8.5 to €8.84) in 2017. (iv) Each band corresponds to a 95 percent confidence interval. (v) The standard errors are clustered at the plant level.

Figure A3.1 plots the point estimates of β_k. Similar to Butschek (2022b), we find that the fraction of workers with an hourly wage below €8.5 significantly drops, whereas the fraction of workers with an hourly wage above the cutoff (by less than €4) significantly increases, thus confirming the validity of our treatment.

A3.3 Additional Tables

Table A3.1: Minimum Wage and Robot Adoption: Binary Treatment

Dependent variable	Robot-use Dummy		Number of Robots			
Sample	w/o 2014 users		w/o 2014 users		w/ 2014 users	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: At Least 3 Workers Affected ($Bite \geq 3$)					
T×Post	0.0086***	0.0065***	0.0111***	0.0081***	0.0168***	0.0117***
	(0.0024)	(0.0024)	(0.0030)	(0.0030)	(0.0033)	(0.0032)
log(Emp)×Post		0.0063***		0.0085***		0.0142***
		(0.0013)		(0.0019)		(0.0022)
N	26200	26200	26193	26193	27253	27253
	Panel B: At Least 5 Workers Affected ($Bite \geq 5$)					
T×Post	0.0109***	0.0082***	0.0138***	0.0099***	0.0203***	0.0139***
	(0.0027)	(0.0027)	(0.0034)	(0.0033)	(0.0038)	(0.0036)
log(Emp)×Post		0.0069***		0.0097***		0.0156***
		(0.0015)		(0.0022)		(0.0025)
N	22670	22670	22664	22664	23584	23584
	Panel C: At Least 10 Workers Affected ($Bite \geq 10$)					
T×Post	0.0133***	0.0099***	0.0157***	0.0112***	0.0213***	0.0146***
	(0.0033)	(0.0035)	(0.0040)	(0.0043)	(0.0044)	(0.0045)
log(Emp)×Post		0.0062***		0.0081***		0.0121***
		(0.0018)		(0.0025)		(0.0027)
N	17945	17945	17939	17939	18669	18669

Notes: (i) This table reports the OLS estimates based on Equation (3.1). (ii) The dependent variable is the dummy of robot use in Columns (1) and (2) and the number of robots with IHS transformation in Columns (3)–(6). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1)–(4) and with the 2014 users for Columns (5) and (6). (iv) The treatment dummy $T = 1$ if at least 3/5/10 workers (in Panels A/B/C) are affected by the minimum wage and $T = 0$ if a plant has no workers affected so the control group is always the same as in Table 3.2. The post dummy $Post = 1$ if year $t \geq 2015$. (v) Log(Emp) is the total number of workers in log at the plant level in 2013. (vi) Both plant and calendar year fixed effects are included. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3.2: Minimum Wage and Robot Adoption: Dynamic Setting

Dependent variable	Robot-use Dummy		Number of Robots			
Sample	w/o 2014 users		w/o 2014 users		w/ 2014 users	
	(1)	(2)	(3)	(4)	(5)	(6)
T×2015	0.0026*	0.0018	0.0025	0.0015	0.0054***	0.0038**
	(0.0015)	(0.0015)	(0.0018)	(0.0018)	(0.0019)	(0.0019)
T×2016	0.0060***	0.0045**	0.0079***	0.0059**	0.0113***	0.0080***
	(0.0022)	(0.0022)	(0.0025)	(0.0025)	(0.0028)	(0.0027)
T×2017	0.0078***	0.0057**	0.0103***	0.0072**	0.0156***	0.0104***
	(0.0026)	(0.0026)	(0.0034)	(0.0034)	(0.0037)	(0.0036)
T×2018	0.0133***	0.0098***	0.0201***	0.0147***	0.0288***	0.0208***
	(0.0034)	(0.0035)	(0.0043)	(0.0042)	(0.0047)	(0.0045)
log(Emp)×2015		0.0026***		0.0032***		0.0051***
		(0.0009)		(0.0011)		(0.0012)
log(Emp)×2016		0.0051***		0.0065***		0.0104***
		(0.0012)		(0.0016)		(0.0019)
log(Emp)×2017		0.0068***		0.0103***		0.0162***
		(0.0014)		(0.0022)		(0.0024)
log(Emp)×2018		0.0114***		0.0173***		0.0250***
		(0.0019)		(0.0029)		(0.0031)
N	33580	33580	33573	33573	34918	34918

Notes: (i) This table reports the OLS estimates based on Equation (3.1), but using calendar years instead of the post period dummy. (ii) The dependent variable is the dummy of robot use in Columns (1) and (2) and the number of robots with IHS transformation in Columns (3)–(6). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1)–(4) and with the 2014 users for Columns (5) and (6). (iv) The treatment dummy is $T = 1$ if at least one worker is affected by the minimum wage, and the calendar years are 2014 to 2018. (v) Log(Emp) is the total number of workers in log at the plant level in 2013. (vi) Both plant and calendar year fixed effects are included. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3.3: Minimum Wage and Robot Adoption: Continuous Treatment

Dependent variable	Robot-use Dummy		Number of Robots			
Sample	w/o 2014 users		w/o 2014 users		w/ 2014 users	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: The Gap Measure per Worker					
Gap×Post	0.0004	0.0009***	0.0004	0.0011***	0.0002	0.0013***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
log(Emp)×Post		0.0075***		0.0105***		0.0157***
		(0.0012)		(0.0018)		(0.0020)
	Panel B: The Fraction of Workers Affected					
N×Post	0.0136**	0.0239***	0.0142**	0.0286***	0.0108	0.0325***
	(0.0056)	(0.0059)	(0.0070)	(0.0074)	(0.0074)	(0.0077)
log(Emp)×Post		0.0080***		0.0111***		0.0164***
		(0.0013)		(0.0019)		(0.0021)
N	33580	33580	33573	33573	34918	34918

Notes: (i) This table reports the OLS estimates based on Equation (3.2). (ii) The dependent variable is the dummy of robot use in Columns (1) and (2) and the number of robots with IHS transformation in Columns (3)–(6). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1)–(4) and with the 2014 users for Columns (5) and (6). (iv) In both panels, Gap and N are normalized by the plant-level employment in 2013. (v) Log(Emp) is the total number of workers in log at the plant level in 2013. (vi) Both plant and calendar year fixed effects are included. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3.4: The Role of Occupation Composition: Robustness Checks

Dependent variable	Robot-use Dummy	Number of Robots	
Sample	w/o 2014 users	w/o 2014 users	w/ 2014 users
	(1)	(2)	(3)
	Panel A: The Gap Measure (IHS): Simple Manual vs Other		
$\text{Gap}^{\text{sm}}\times$Post	0.0041***	0.0046***	0.0062***
	(0.0013)	(0.0017)	(0.0017)
$\text{Gap}^{\text{oth}}\times$Post	0.0005	0.0008	0.0005
	(0.0004)	(0.0006)	(0.0007)
log(Emp)$\times$Post	0.0064***	0.0092***	0.0139***
	(0.0012)	(0.0017)	(0.0019)
$\text{Share}^{\text{sm}}\times$Post	0.0244***	0.0326***	0.0544***
	(0.0087)	(0.0122)	(0.0132)
N	33580	33573	34918
	Panel B: The Bite Measure (IHS): Simple Manual vs Other		
$\text{N}^{\text{sm}}\times$Post	0.0085***	0.0094***	0.0115***
	(0.0027)	(0.0034)	(0.0035)
$\text{N}^{\text{oth}}\times$Post	0.0008	0.0009	0.0001
	(0.0008)	(0.0012)	(0.0014)
log(Emp)$\times$Post	0.0063***	0.0091***	0.0139***
	(0.0012)	(0.0018)	(0.0020)
$\text{Share}^{\text{sm}}\times$Post	0.0201**	0.0282**	0.0511***
	(0.0093)	(0.0127)	(0.0138)
N	33580	33573	34918
	Panel C: The Gap Measure (IHS): Replaceable vs Non-replaceable		
$\text{Gap}^{\text{repl}}\times$Post	0.0060***	0.0062**	0.0081**
	(0.0022)	(0.0030)	(0.0032)
$\text{Gap}^{\text{non-repl}}\times$Post	-0.0031**	-0.0029*	-0.0042**
	(0.0013)	(0.0018)	(0.0019)
log(Emp)$\times$Post	0.0066***	0.0091***	0.0141***
	(0.0012)	(0.0017)	(0.0019)
Replaceability$\times$Post	0.1132***	0.1395***	0.2135***
	(0.0185)	(0.0254)	(0.0273)
N	33435	33428	34768

Notes: (i) This table reports the OLS estimates based on Equation (3.4). (ii) The dependent variable is the dummy of robot use in Column (1) and the number of robots with IHS transformation in Columns (2) and (3). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1) and (2) and with the 2014 users for Column (3). (iv) The continuous treatment is the gap measure (IHS transformed) in Panel A, and the number of workers affected (IHS transformed) in Panel B, separately constructed for the simple manual occupations and for other occupations. In panel C, the Gap measure is decomposed into the replaceable and non-replaceable components through the occupation-level share of replaceable tasks matched with worker-level Gap measures. The post dummy $Post = 1$ if year $t \geq 2015$. (v) Log(Emp) is the total number of workers in log at the plant level in 2013; Share^{sm} is the share of simple manual workers in 2013; Replaceability is the plant-level average share of replaceable tasks. (vi) Both plant and calendar year fixed effects are included. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3.5: Sample Selection

Dependent variable	Robot-use Dummy	Number of Robots	
Sample	w/o 2014 users	w/o 2014 users	w/ 2014 users
	(1)	(2)	(3)
	Panel A: Excluding Automobile Industry		
Gap×Post	0.0016***	0.0021***	0.0022***
	(0.0005)	(0.0006)	(0.0007)
Gap$^{\text{sm}}$×Post	0.0059***	0.0070***	0.0092***
	(0.0010)	(0.0014)	(0.0014)
Gap$^{\text{oth}}$×Post	-0.0001	-0.0001	-0.0010
	(0.0004)	(0.0006)	(0.0007)
N	33145	33138	34328
	Panel B: Including Only Robot-Intensive Industries		
Gap×Post	0.0014	0.0016	0.0020*
	(0.0008)	(0.0010)	(0.0011)
Gap$^{\text{sm}}$×Post	0.0055***	0.0067***	0.0095***
	(0.0012)	(0.0016)	(0.0016)
Gap$^{\text{oth}}$×Post	-0.0010	-0.0015	-0.0029**
	(0.0008)	(0.0010)	(0.0012)
N	18020	18015	19300
	Panel C: Excluding High-Wage Control Group Plants		
Gap×Post	0.0017***	0.0020***	0.0022***
	(0.0006)	(0.0008)	(0.0008)
Gap$^{\text{sm}}$×Post	0.0057***	0.0068***	0.0097***
	(0.0010)	(0.0014)	(0.0014)
Gap$^{\text{oth}}$×Post	-0.0001	-0.0003	-0.0015*
	(0.0005)	(0.0008)	(0.0009)
N	28630	28626	29816
	Panel D: Excluding Plants with < 50 Employees		
Gap×Post	0.0021**	0.0027**	0.0034***
	(0.0009)	(0.0011)	(0.0012)
Gap$^{\text{sm}}$×Post	0.0085***	0.0102***	0.0148***
	(0.0017)	(0.0023)	(0.0023)
Gap$^{\text{oth}}$×Post	-0.0007	-0.0006	-0.0023*
	(0.0008)	(0.0011)	(0.0012)
N	15970	15966	16941

Notes: (i) This table reports the OLS estimates based on Equations (3.2) and (3.4). (ii) The dependent variable is the dummy of robot use in Column (1) and the number of robots with IHS transformation in Columns (2) and (3). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1) and (2) and with the 2014 users for Column (3). (iv) The continuous treatment is the gap measure (IHS transformed), and in the second regression for each panel, its decomposition is into simple manual occupations and other occupations. The post dummy $Post = 1$ if year $t \geq 2015$. (v) Panel A drops the automobile industry; Panel B only includes relatively robot-intensive industries (manufacturing, agriculture, wholesale/retail trade, building/installation, human health); Panel C drops plants with less than 50 employees in 2013; Panel D drops control group plants whose average wage in 2013 is above the control group median. (vi) Plant and calendar year fixed effects and log(Emp) are included in all specifications. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3.6: Hourly Wage and Minimum Wage Exposure

Dependent variable	Robot-use Dummy	Number of Robots	
Sample	w/o 2014 users	w/o 2014 users	w/ 2014 users
	(1)	(2)	(3)
	Panel A: 7.5 Hours per Day for Full-time Workers		
Gap×Post	0.0016***	0.0021***	0.0025***
	(0.0005)	(0.0006)	(0.0007)
Gap^{sm}×Post	0.0064***	0.0078***	0.0110***
	(0.0012)	(0.0015)	(0.0015)
Gap^{oth}×Post	-0.0002	-0.0002	-0.0012
	(0.0005)	(0.0006)	(0.0007)
N	33580	33573	34918
	Panel B: Hourly Wage in 2012		
Gap×Post	0.0018***	0.0022***	0.0028***
	(0.0005)	(0.0007)	(0.0007)
Gap^{sm}×Post	0.0059***	0.0071***	0.0101***
	(0.0011)	(0.0014)	(0.0014)
Gap^{oth}×Post	-0.0002	-0.0002	-0.0010
	(0.0004)	(0.0006)	(0.0007)
N	32660	32653	33988
	Panel C: Excluding Workers with Hourly Wage below 4 Euros		
Gap×Post	0.0016***	0.0018***	0.0023***
	(0.0005)	(0.0007)	(0.0007)
Gap^{sm}×Post	0.0057***	0.0067***	0.0097***
	(0.0010)	(0.0014)	(0.0014)
Gap^{oth}×Post	-0.0002	-0.0003	-0.0012*
	(0.0005)	(0.0006)	(0.0007)
N	33550	33543	34888
	Panel D: Including All Workers with Positive Hourly Wage		
Gap×Post	0.0015***	0.0019***	0.0024***
	(0.0005)	(0.0006)	(0.0006)
Gap^{sm}×Post	0.0056***	0.0067***	0.0097***
	(0.0010)	(0.0013)	(0.0013)
Gap^{oth}×Post	-0.0001	-0.0001	-0.0010
	(0.0004)	(0.0006)	(0.0007)
N	33605	33598	34943

Notes: (i) This table reports the OLS estimates based on Equations (3.2) and (3.4). (ii) The dependent variable is the dummy of robot use in Column (1) and the number of robots with IHS transformation in Columns (2) and (3). (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Columns (1) and (2) and with the 2014 users for Column (3). (iv) The continuous treatment is the gap measure (IHS transformed), and in the second regression for each panel, its decomposition is into simple manual occupations and other occupations. The post dummy $Post = 1$ if year $t \geq 2015$. (v) Panel A assumes 7.5 hours per day for full-time workers; Panel B uses 2012 worker-level data for wage construction; Panel C drops workers whose hourly wage is below 4 euros in 2013; Panel D includes all workers with a positive wage in 2013. (vi) Plant and calendar year fixed effects and log(Emp) are included in all specifications. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3.7: Main Variables in Percentile

Dependent variable	Number of Robots in Percentile	
Sample	w/o 2014 users (1)	w/ 2014 users (2)
	Panel A: The Gap Measures in IHS	
Gap×Post	0.1638***	0.1428***
	(0.0449)	(0.0437)
Gap^{sm}×Post	0.5463***	0.4677***
	(0.0980)	(0.0878)
Gap^{oth}×Post	-0.0016	-0.0051
	(0.0422)	(0.0417)
N	33573	34918
	Panel B: The Gap Measures in Percentile	
Gap×Post	0.0115***	0.0099***
	(0.0033)	(0.0032)
Gap^{sm}×Post	0.0244***	0.0210***
	(0.0044)	(0.0040)
Gap^{oth}×Post	0.0012	0.0009
	(0.0030)	(0.0029)
N	33573	34918

Notes: (i) This table reports the OLS estimates based on Equations (3.2) and (3.4). (ii) The dependent variable is the number of robots measured in percentile. (iii) The regression sample consists of the plants that did not use robots in 2014 without the incumbent 2014 robot users for Column (1) and with the 2014 users for Column (2). (iv) The continuous treatment is the gap measure, and in the second regression for each panel, its decomposition is into simple manual occupations and other occupations. The post dummy $Post = 1$ if year $t \geq 2015$. (v) Panel A uses gap measures with IHS transformation, and Panel B uses gap measures in percentile. (vi) Plant and calendar year fixed effects and log(Emp) are included in all specifications. (vii) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3.8: Main Regressions with only Incumbent Users

Dependent variable: Number of Robots in log			
Binary Treatment (T)		Continuous Treatment (Gap)	
T×Post	0.0744* (0.0399)	Gap×Post	0.0070 (0.0066)
T^{sm}×Post	0.0896** (0.0423)	Gap^{sm}×Post	0.0123 (0.0076)
T^{oth}×Post	0.0430 (0.0523)	Gap^{oth}×Post	-0.0049 (0.0083)

Notes: (i) This table reports the OLS estimates based on Equations (3.1)–(3.4). (ii) The dependent variable is the number of robots measured in log. (iii) The regression sample consists only of plants that already use robots in 2014 ($N = 1339$). (iv) The gap measures are IHS transformed. The post dummy $Post = 1$ if year $t \geq 2015$. (v) Plant and calendar year fixed effects and log(Emp) are included in all specifications. (vi) Standard errors clustered at the plant level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Chapter 4

Robots, Occupations, and Worker Age: A Production-Unit Analysis of Employment[1]

4.1 Introduction

The impact of new technology on the labor market is one of the oldest and most widely discussed topics in economics. Recent technological advances in robotics again spark high hopes and dire fears at the same time. Those being more on the enthusiastic side hope that robots may play an important role in overcoming growing labor shortages in aging societies. Pessimists fear that robots will destroy decently paid middle-class jobs in unprecedented magnitudes. Whether such hopes and fears ever materialize only partly depends on whether robots are substitutes or complements for *gross* labor input. As robots could be substitutes for certain labor inputs, e.g. for workers least adaptable to change and for those performing routine tasks, but complements for others, e.g. for those supervising robots and production processes such as engineers or managers, it is even more important to understand the impact of robotization on workforce *composition*. Aging societies lacking young workers will benefit more from robots substituting for young workers and societies with abundant high-skilled labor will benefit more from robots complementing those workers and taking over routine tasks. As robots could have very different effects on, say, young production workers versus young engineers, the young generation making its occupational decisions should consider how robots may substitute or complement their jobs in order to make informed choices.

[1] This chapter is joint work with Liuchun Deng, Steffen Müller, and Jens Stegmaier. A previous version was published as IZA Discussion Paper (No. 16128, 2023) under the same title.

We will argue theoretically and demonstrate empirically that robot adoption has very heterogeneous effects by occupation and worker age. Based on the seminal work of Acemoglu and Restrepo (2018), we build a task-based model of robot adoption to examine the effects of robot adoption on workforce composition through both displacement and reinstatement channels. The latter hinges on workers' (differential) ability to adapt to new tasks. We take on board the basic implications of human capital theory and core findings of the cognitive science literature on fluid and crystalline intelligence and predict that young workers are complements to technological change.

Individual robot-using firms decide on which workers to hire or to replace. Documenting heterogeneous effects of robots thus requires granular micro-level data on robot use, workers' occupation, age, and tasks. While the number of micro-level studies is growing, most existing studies utilize industry-level variation in robots and therefore cannot test whether robots and certain groups of workers are substitutes or complements at the level of the production unit.[2] Core contributions adopt a local labor market (LLM) approach (Acemoglu and Restrepo, 2020a, Dauth et al., 2021). Whereas firm-level evidence allows directly observing the technological relationship between robot technology and various labor inputs, i.e. it reveals which types of labor are complements and substitutes to robot technology in production, the LLM perspective mixes the user firm reaction with the competitive reaction of other firms. The LLM approach is thus informative on the gross employment effect at the market level but not on the production-level technological relationship between robots and various labor inputs.

To make progress in this important topic, we developed and integrated a battery of questions on robot use into Germany's leading establishment panel survey, the IAB Establishment Panel. Whereas most other micro-level analyses around the world had to rely on robot imports, we are among the very first papers observing actual robot *use*

[2] Starting from the seminal paper by Graetz and Michaels (2018), a vast literature uses industry-level robot data (mainly provided by the International Federation of Robotics (IFR)) to study the labor market effects of robots. For notable contributions, see de Vries et al. (2020), Faber (2020), Aksoy et al. (2021), and Adachi et al. (2024), among many others.

in production.[3] A further unique feature of our data is that we are able to connect it to high-quality social security records, which circumvents common survey data issues with sample attrition and allows us to analyse robots' impact on employment composition and worker turnover in terms of worker age and occupation. Using detailed data on worker tasks, we assign job tasks to occupation-age groups, which enables us to confront our empirical results with our task-based framework. In doing so, we also provide first plant-level evidence on whether robots are indeed substitutes for routine manual occupations and complements for non-routine occupations as predicted by task-based models and generally assumed in the robot literature.

Our study is among the first in analyzing the effects of plant-level robot adoption in Germany, which is a large technologically advanced economy that ranks among the top robot users in the world. Unlike the US, Germany resorts to a highly developed apprenticeship training system and managed to preserve its industrial core even during the recent decades of import competition from China and other low-income countries (Dauth et al., 2014) by focusing on high-quality manufacturing and exporting. Little is known about the firm-level impact of robots on the German economy. Deng et al. (2023) use the same survey data as we do and are first in describing establishment-level robot adoption in Germany. They find robot adoption to be rare and very concentrated within a few industries. Larger firms are more likely to use and adopt robots.[4]

There is no study using establishment panel data on robot use to study jointly the micro effects of robot adoption on workforce composition in terms of occupation and age. We analyze the impact of robot adoption on employment and employment composition by confronting the predictions of our task-based model with event-study analyses of German manufacturing plants following them before and after the first-time

[3] Robot import can be a poor proxy for robot use because many robot importers resell imported robots instead of using them in production (cf. Bonfiglioli et al., 2020, Humlum, 2021). Even if a treatment group of robot-using importers can be identified, some control group firms will source robots from resellers. Robot imports are a flow concept and arriving at a robot stock at firm-level requires assumptions on the depreciation rate. Finally, using robot imports makes little sense when analyzing robot-producing countries, as e.g. Germany. Very recently, firm-level data on robot *use* became available for the US (Acemoglu et al., 2022, Brynjolfsson et al., 2023).

[4] Recently, Benmelech and Zator (2021) use the same data to analyze robot adoption patterns. Their analysis focuses on the effects of robots on overall employment at the plant level and in industry-region cells.

robot adoption. The reason for focusing on first-time robot adopters instead of (usually large) firms buying just another robot is that first-time adoption is more likely to capture a major reorganization of the production process and the labor inputs.

We demonstrate descriptively that the task content of work determines replaceability primarily along the occupational dimension and much less so along the age dimension. We document rising employment upon robot adoption reinforcing firm-level results by Acemoglu et al. (2020), Bonfiglioli et al. (2020), Dixon et al. (2019), and Koch et al. (2021). In line with theoretical perceptions, robot adoption is more beneficial for the least routine-intensive occupations. In particular, employment increases among technicians, engineers, and managers. Workers performing routine manual tasks see their employment opportunities unchanged. This task bias confirms core predictions of the standard task-based models (D. H. Autor et al., 2003, Acemoglu and Restrepo, 2018) in the robot context at the production-unit level. Results are also in line with Dauth et al. (2021) who use industry-level variation in robot intensity across German local labor markets. We find that the increase in total employment and in the shares of technicians, engineers, and managers is achieved by adopting firms' increased hiring but unchanged worker attrition. Constant employment levels for low-skilled manual workers, however, mask increased churning for this group, confirming another prediction of our model.

Importantly, the fraction of younger workers *increases* after robot adoption because of intensified hiring of young workers. This confirms the predictions of cognitive science literature on adaptability to new tasks by age as well as standard predictions of human capital theory. This result sheds new light on the findings by Dauth et al. (2021) who document that a decrease in the hiring of younger workers is associated with robot exposure in their local labor market setting, which could imply that, within automating industries, those firms that do not adopt robots hire fewer young workers. When analyzing the occupation and age dimensions jointly, we find that young workers' employment rises among low- and middle-skilled workers whereas the employment increase for technicians/engineers and managers is concentrated among middle-aged and older workers, respectively. In sum, our results support hypotheses that robots are complements to high-skilled labor and to younger workers and offer a nuanced view on very heterogeneous effects of age by occupation. Through the lens of our model and the concepts of displacement and reinstatement effects theorized by Acemoglu and Restrepo (2018), our results imply that the displacement effect of robots is primarily occupation-dependent (i.e. task-dependent) whereas the reinstatement effect (or "new task channel") mostly depends on workers' age.

We contribute to the growing firm-level robot literature on employment effects. Using firm-level data on robot *imports* for France, Bonfiglioli et al. (2020) find mostly statistically insignificant pre-post adoption changes in employment.[5] Acemoglu et al. (2020) use similar data but back them up with additional data sources and look at the 2010-2015 period. They find positive effects on employment and argue that the positive employment effect masks reallocation effects where adopters grow at the expense of non-adopters. Humlum (2021) finds increased employment in Denmark. To overcome issues of robot import data, a recent wave of studies leverage on data on robot *use* at the production unit level. Koch et al. (2021) employ firm-level panel data for the Spanish manufacturing sector containing a robot use question (yes/no). Applying event-study estimates, Koch et al. (2021) report positive short- and medium-run effects of robot adoption on output and employment. Acemoglu et al. (2022) exploit a new technology module of the 2019 Annual Business Survey in the US. They show descriptively that robot users self-report negligible employment effects.[6] We add to this literature a study on employment for a major Western economy using high-quality data on robot use (instead of imports) and support the generally favorable effects of robot adoption found earlier. We are among the first to show that this employment increase goes hand in

5 Their IV procedure yields relatively weak first-stage F-statistics while second-stage results display huge point estimates (e.g. value added per worker increases by $100 \times (-1 + e^{1.19}) = 230\%$ after robot adoption whereas employment is reduced by 43%).

6 Aghion et al. (2023) and Bessen et al. (2019) use firm-level data on automation expenditures. The data does not allow them to disentangle robots from the various other automation techniques. Similarly, Dinlersoz and Wolf (2018) use aggregated technology categories in their analysis of US establishments.

hand with a sharp increase in worker churning for the most routine task intensive occupations.

We further contribute to the literature on the micro effects of robots on skill composition.[7] Barth et al. (2020) combine import data for Norwegian manufacturing firms with worker-level data to analyze within-firm wage inequality. Robotization yields a wage premium for college education and managers implying that robots are complements to skill and managerial tasks. Dixon et al. (2019) merge Canadian robot import data with surveys on employment and workforce composition and find an increase in worker turnover, positive overall employment effects, and a decline in managerial headcount. Humlum (2021) reports a decline in the wage bill and the employment shares of production workers relative to tech workers after robot adoption. Koch et al. (2021) report positive short- and medium-run effects of robot adoption on employment of both high- and low-skilled workers. Acemoglu et al. (2022) report an increase in skill demand among robot-using firms. In work parallel to ours, Acemoglu et al. (2023) use data on robot imports in the Netherlands and combine it with various measures of worker replaceability to analyze the impact of robot adoption on workforce composition. Their results on overall employment effects are similar to ours and they also report worse employment outcomes for workers performing routine or replaceable tasks. They do not look at worker turnover and worker age. We add to this literature by directly analyzing the *occupational* dimension of employment. By showing that the least routine manual task intensive occupations, in particular supervising occupations, experience the strongest employment gains upon robot adoption, our results support a core theoretical concept of the task-based literature.

Finally, we contribute to the literature by asking how new technologies interact with worker age ("age-biased technological change"). Acemoglu and Restrepo (2018) formalize the reinstatement effect of new technologies postulating that new technologies lead to employment growth because of the new tasks they create. New tasks created

7 Acemoglu and Restrepo (2020b) discuss theoretically how displacement and reinstatement effects of automation can lead to a skill bias and present corresponding aggregate sector-level evidence for the US.

through new technologies require adaptability on the side of workers. The theoretical foundations for potential age biases in the adaptability to new technology come from human capital theory and cognitive science. The former predicts higher investments into young workers' new technology skills because young workers have a longer payoff horizon for human capital investments. Cognitive science distinguishes between fluid and crystalline abilities (or "intelligences") and shows that the two abilities have very different age profiles.[8] Fluid abilities include perceptual speed and reasoning abilities and are conducive to the speed of finding solutions to new problems. They rapidly decline with age.

Studies tend to confirm that older individuals are less able to adapt to changes (Bosma et al., 2003). Due to their superior fluid abilities, young workers have a comparative advantage in adapting to new tasks. In line with those predictions from cognitive science and gerontology, Aubert et al. (2006) find that new technologies enhance not only hires of younger workers in general[9] but also increase employment opportunities for young blue-collar workers. We will find exactly the same mechanisms upon robot adoption. Bartel and Sicherman (1993) start from a human capital investment perspective and find that an unexpected increase in the rate of technological change will decrease the employment of older workers. The reason is that retraining investments for older workers have a shorter pay-off horizon than those for younger workers, which makes the former comparatively less attractive for investments. Lipowski (2023) documents that a shortage in the supply of young workers in Germany hinders plant-level technology adoption and rationalizes the finding through the comparative advantage of skill acquisition for young workers.

[8] The general theory of fluid and crystallized intelligence is often attributed to Cattell (1971) and builds on several earlier contributions of the author, e.g. Horn and Cattell (1966).

[9] Vintage human capital models provide an additional explanation for some of these findings. According to those models, robot-adopting firms may hire more young workers because young workers' up-to-date knowledge may be a complement to new technology (Chari and Hopenhayn, 1991).

4.2 Model

In this section, we introduce a simple model of robot adoption to guide our empirical analysis.[10] The model features a task-based framework as in Acemoglu and Restrepo (2018). The baseline setup reproduces the prediction of self-selection into robot adoption and an overall ambiguous employment effect as in Koch et al. (2021) and Bonfiglioli et al. (2020), with an added prediction of increased churning. The main departure is an elaboration of the effects on workplace composition by incorporating the occupation and age dimensions.[11] The effects on workforce composition hinge on two margins of adjustment: workers' specialization in *existing* tasks and their differential adaptability to *new* tasks. In light of our model and empirical evidence based on the German task data, we will argue that the former drives the change in occupational structure through the displacement channel, whereas the latter is the primary cause of the shift in the age profile through the reinstatement channel.

4.2.1 Baseline Setting

We consider a partial equilibrium setting. Each firm faces the same iso-elastic demand $y_i = \zeta p_i^{-\eta}$, where $\eta > 1$ is the price elasticity, y_i is the demand for firm i, p_i is the price charged by firm i, and ζ is a demand shifter, which is assumed for simplicity to be the same across firms. The supply-side specification follows the standard task-based framework: $y_i = \phi_i \left(\int_0^1 s_i(j)^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}j \right)^{\frac{\sigma}{\sigma-1}}$, where y_i is firm i's output, ϕ_i is the firm-specific productivity, $s_i(j)$ is the input of task j, and σ is the elasticity of substitution. It should be noted that given the homothetic production function, any demand shocks to ϕ_i would not directly change the plant-level occupation composition or age profile as we will introduce in what follows.

[10] All formal results and proofs for the model section are relegated to the Appendix.

[11] Koch et al. (2021) introduce in their model different types of labor by skill level and Humlum (2021) puts occupations and occupational choice on the center stage of his analysis. We go beyond the occupation dimension by further introducing worker age and also discussing the interplay between occupation and age.

Tasks are either routine or non-routine. Denote the set of routine tasks by $\mathcal{R} \subseteq [0,1]$ and the share of routine tasks by θ ($\theta \equiv \int_{\mathcal{R}} \mathrm{d}j$). Routine tasks are technologically automatable and can be performed by either robots or human labor, whereas non-routine tasks are not automatable and can only be performed by human labor. Firm i's input of task j is given by

$$s_i(j) = \begin{cases} \ell_i(j) + \lambda k_i(j) & j \in \mathcal{R} \\ \ell_i(j) & j \notin \mathcal{R} \end{cases},$$

where $\ell_i(j)$ is the employment of human labor and $k_i(j)$ is the robot input, both used in task j. Robots, which can only be used for routine tasks, are perfect substitutes for human labor. The parameter $\lambda > 0$ measures the efficiency of robots relative to workers. The wage rate w and the rental rate of robots r are exogenously given.[12] We assume $r < \lambda w$, implying that if firm i chooses to adopt robots, it would replace human labor with robots for all routine tasks. Robot adoption incurs a one-time fixed cost F. Because the saving in variable production costs increases with the firm size, only firms that are sufficiently productive and large are willing to pay the fixed cost and adopt robots.

The effect of robot adoption on overall firm-level employment is generally ambiguous, in line with the predictions in Graetz and Michaels (2018) and Acemoglu and Restrepo (2018). Robots, on the one hand, replace workers who perform routine tasks (displacement effect), but on the other hand, may increase the demand for workers who perform tasks complementary to robots (productivity effect). If the degree of complementarity between different tasks is sufficiently high (σ sufficiently small), then the second channel can potentially dominate the first and the overall employment effect at the firm level turns positive.

Implication 1. *Robot adoption has an ambiguous effect on firm-level employment.*

[12] Acemoglu and Restrepo (2021) consider an elegant setting in which wage rates are endogenous and can be expressed as functions of task shares. Since our empirical exercise focuses on the employment effects instead of wage effects, we abstract from the endogenization of the wage rates.

Because of the direct displacement effect of robots, job separation is expected to increase following adoption. If the productivity effect is present, hiring will also increase.[13]

Implication 2. *If the effect of robot adoption on overall employment is positive, then both hiring and job separation rates are expected to increase.*

4.2.2 Effects on Workforce Composition: Displacement Channel

Robots replace workers performing routine tasks. Because the task content varies with jobs, robot adoption can directly affect workforce composition through the task displacement channel. To investigate the effects on workforce composition, we enrich the model by introducing in turn the occupation and age dimensions.[14]

4.2.2.1 The Occupation Dimension

We first introduce the occupation dimension. Our formulation follows the task-based model that appeared in Humlum (2019) and both specifications would yield qualitatively similar reduced-form production functions. There are O occupations with a generic element $o \in \mathcal{O} \equiv \{1, 2, ..., O\}$. For each task j, $o(j)$ denotes the occupation that performs task j. We define the share of tasks performed by occupation o simply as $\mu_o \equiv \int_0^1 \mathbb{1}(o(j) = o)\,\mathrm{d}j$ ($\mathbb{1}$ is the indicator function). Within the set of tasks performed by occupation o, we further define the share of routine tasks as

$$\theta_o \equiv \frac{\int_{\mathcal{R}} \mathbb{1}(o(j) = o)\,\mathrm{d}j}{\int_0^1 \mathbb{1}(o(j) = o)\,\mathrm{d}j},$$

[13] We abstract from re-training of workers within firms. Re-training would mute the effect of robot adoption on churning. Empirically, we do not find a change in training intensity around robot adoption.

[14] In principle, robot adoption can also affect occupational composition through differential productivity effects, but since we do not have a direct measure of productivity effects at the task level and there is no strong theoretical predication about how productivity effects vary with occupation or age a priori, we focus solely on the displacement effect in this subsection.

where we recall $\mathcal{R}$ is the set of routine tasks. As an occupation-level replaceability index, θ_o captures the extent to which robots affect an occupation through the displacement channel.

As we will describe later using the German survey data, the share of tasks replaceable by robots varies with occupation.[15] Engineering and managerial occupations, for instance, perform a relatively low share of routine tasks (small θ_o) and therefore are more likely to experience an expansion in employment opportunies.

Implication 3. *Robot adoption is more likely to raise employment for occupations that perform more non-routine tasks.*

Similar to the argument for the overall employment change, if the effect of robot adoption on employment in a particular occupation is positive, both hiring and job separations for that occupation are likely to increase as well.

4.2.2.2 The Age Dimension

We further incorporate the age dimension. Following Acemoglu and Restrepo (2022), we assume workers of different ages have comparative advantage in performing different tasks and are thus sorted into different tasks. But unlike their focus on the demographics as drivers of robot adoption, we examine instead how robot adoption affects the age profile.

There are A age groups with a generic element $a \in \mathcal{A} \equiv \{1, 2, ..., A\}$. A younger age group takes a lower index from $\mathcal{A}$. For each task j, $a(j)$ denotes the age group that performs task j. Correspondingly, we define the share of tasks performed by age group a as $\mu^a \equiv \int_0^1 \mathbb{1}(a(j) = a)\,\mathrm{d}j$ and the share of tasks performed by age group a and occupation o as $\mu_o^a \equiv \int_0^1 \mathbb{1}(a(j) = a, o(j) = o)\,\mathrm{d}j$. We also define at both age and age-occupation levels the replaceability index as

$$\theta^a \equiv \frac{\int_{\mathcal{R}} \mathbb{1}(a(j) = a)\,\mathrm{d}j}{\int_0^1 \mathbb{1}(a(j) = a)\,\mathrm{d}j} \quad \text{and} \quad \theta_o^a \equiv \frac{\int_{\mathcal{R}} \mathbb{1}(a(j) = a, o(j) = o)\,\mathrm{d}j}{\int_0^1 \mathbb{1}(a(j) = a, o(j) = o)\,\mathrm{d}j}.$$

[15] It has been documented in the literature that the replaceability of workers by robots varies systematically with occupation (and industry), see Graetz and Michaels (2018) and also Chapter 4.2 of the IFR report *World Robotics: Industrial Robots 2018*.

The employment effect by age group through the displacement channel hinges on θ^a and θ^a_o. As we will explain in more detail in Section 4.1, the German survey data suggests that within each occupation, the share of routine tasks is relatively stable across age groups, and across occupations, the age profile of employment is similar. Those two empirical observations motivate two assumptions: $\theta^a_o = \theta_o$ for any a and $\mu^a = \mu^a_o/\mu_o$ for any o. It is straightforward to show that the two assumptions further imply $\theta^a = \theta$. Since the replaceability index does not vary with age either in aggregate or at the occupation levels, robot adoption is not expected to affect either the overall or occupation-level age profile through the displacement channel.

4.2.3 Effects on Workforce Composition: Reinstatement Channel

To further explore the potential effects of robot adoption on the age profile, we now consider the reinstatement channel as formalized in Acemoglu and Restrepo (2018). Robot adoption introduces new tasks into the production processes.[16] Those new tasks will be performed by human labor and workers (of different age groups) face the challenge of adapting to the new tasks in a robotized production setting. We depart from the literature by explicitly considering age bias in workers' adaptability to new tasks. We will consider in turn occupation-neutral and occupation-specific age biases and discuss their empirical implications.

4.2.3.1 Occupation-Neutral Age Bias in Adaptability

Young workers are in general more adaptable to new tasks because of cognitive advantages in adaptability (Bosma et al., 2003), their newer human capital vintage (Chari and Hopenhayn, 1991), and the higher willingness to acquire needed human capital coming from longer payoff horizons for human capital investment (Heckman and Jacobs, 2011). This higher adaptability is primarily tied to worker age. Formally, new tasks of measure δ are introduced after robot adoption. For any new task $j \in (1, 1+\delta]$, $a(j)$ is

[16] The new tasks under automation include tasks of operating and programming robots and also technical maintenance work. Also see Hirvonen et al. (2022) for empirical evidence on how firms use new production technologies to produce new products, which may lead to the introduction of new tasks.

the age group that performs j. The measure of new tasks performed by age group a is defined as $\nu^a \equiv \int_1^{1+\delta} \mathbb{1}(a(j) = a)\,\mathrm{d}j$. Thus, (ν^a/μ^a) measures (relative) adaptability of age group a to new tasks. Formally, we assume that (ν^a/μ^a) is decreasing in a, that is, younger workers are more adaptable to new tasks. Consequently, the employment change for young workers under robot adoption is more positive (or less negative) than for older workers.

Implication 4. *Robot adoption is more likely to raise the employment of young workers.*

4.2.3.2 Occupation-Specific Age Bias in Adaptability

Finally, we revisit the occupation dimension in the context of age bias in adaptability. Although younger workers enjoy greater adaptability in general, there are certain occupations in which prior experience (or crystalline intelligence) may play a very important role in helping the workers navigate through the change. For those occupations, middle-aged or older workers may see a relative increase in employment following adoption. To formalize this idea, denote by $o(j)$ the occupation that performs new task $j \in (1, 1+\delta]$. For each occupation o and age group a, we can define the new-task adaptability measure (ν_o^a/μ_o^a) with $\nu_o^a \equiv \int_1^{1+\delta} \mathbb{1}(a(j) = a, o(j) = o)\,\mathrm{d}j$. Since within each occupation, there is little variation in replaceability across age groups, the reinstatement channel remains the primary channel through which robot adoption impacts the within-occupation age profile. We can then prove that the relative employment effects by age group within an occupation follow closely the (relative) adaptability measure (ν_o^a/μ_o^a).

Implication 5. *The effect of robot adoption on the employment of different age groups varies with occupation. For occupations in which prior experience plays an important role, the employment of middle-aged or old workers is more likely to increase.*

4.3 Data & Empirical Approach

4.3.1 Data

Our sample is constructed by combining four plant- and worker-level data sets. The plant-level robot data is from the IAB Establishment Panel, an annual survey of nearly 16,000 plants sampled from the population of German plants employing workers subject to social security contributions. The IAB Establishment Panel is a high-quality, long-standing panel that is nationally representative as a whole but also at the sector level, for firm-size classes, and across German federal states.[17] In the 2019 wave, we included a dedicated section on robot use. Our definition of robots follows the ISO definition: *A robot is any automated machine with multiple axes or directions of movement, programmed to perform specific tasks (partially) without human intervention.* The robot question has been intensively pre-tested and carefully designed to make sure that respondents know the difference between robots and other automation techniques such as traditional CNC machines. The survey questions of interest are (1) whether a plant used robots between 2014 and 2018 (extensive margin), and if so, (2) how large the robot stock in each year from 2014 to 2018 was (intensive margin).[18] The latter enables us to distinguish between incumbent robot users, i.e. plants already using robots in 2014, and new robot adopters, i.e. plants that newly adopted this technology after 2014. It additionally allows us to observe the exact year of adoption, which is not possible in the micro-level studies of Koch et al. (2021) and Acemoglu et al. (2022).

The design of the robot question helps us identify robot adopters up to five years in the past and the panel structure of our data allows us to also analyze pre-adoption periods for those plants. In particular, we identify a plant as a robot adopter if it answered zero robots in use in 2014 but a positive number of robots thereafter. The year of robot adoption is thus defined as the first year a robot adopter reported a

[17] For more information on the IAB Establishment Panel, see Bechmann et al. (2019).

[18] An English translation of all survey questions on robots can be found in the Appendix. For more details on the survey design and quality of the robot data, see Plümpe and Stegmaier (2022), and for descriptive analysis on plant-level robot use and adoption in Germany using this data set, see Deng et al. (2023).

positive number of robots in use. By definition, robot adoption in our sample can only take place from 2015 to 2018. However, although the Establishment Panel is a high-quality survey with very high response rates (80% response rate for plants that responded in the previous year), panel attrition reduces the number of panel cases substantially when going back in time for several years. Fortunately, we are able to link our survey plants via unique plant identifiers with administrative data from the IAB Establishment History Panel (BHP), which aggregates social security notifications to the plant level. We are thus able to observe plants for very long time spans without loss of observations.[19]

Our main dependent variables from the BHP are total employment as well as the number of workers in certain occupational and age groups. When forming occupational groups, we follow the Blossfeld categorization provided by the IAB. This widely used occupational categorization is based on Blossfeld (1987) which classifies occupations into a total of 12 groups on the basis of the level of task requirements for the job held. We analyze the following six occupational categories more thoroughly: workers performing simple manual tasks, workers performing qualified manual tasks, engineers and technicians, managers, and service and administrative workers. The BHP additionally provides age categories and we define three groups; i.e. young (20−35 years); middle-aged (35−54); and older (55−65).[20]

Lastly, we are also interested in answering whether robots complement or substitute specific age groups *within* our occupational groups. The BHP plant-level data does not offer interactions between age and occupation and we therefore resort to worker-level data from the IAB Employment History (BeH) that we link with the BHP via unique plant identifiers.[21] For all plants surveyed in the 2019 IAB Establishment Panel wave that answered the extensive margin question on robot use, we merge worker-level information from the BeH for the years from 2012 to 2019. We keep only worker spells

[19] For information on the BHP data, see Ganzer et al. (2021). Note that we use the full population instead of the 50% sample as explained in Ganzer et al. (2021).

[20] Results are very similar when we include workers younger than 20.

[21] The BeH contains all employment spells of workers subject to social security contributions. It is the main data source behind the publicly available SIAB data described in Frodermann et al. (2021).

that cover June 30 to match the plant-level BHP data, which also reports for June 30. Employees are grouped by age with identical cut-offs as described above. To create the Blossfeld occupational categories we use a crosswalk between the latest classification of occupations (KldB2010) to the one on which the original Blossfeld categorization is based (KldB1992). Combining our six occupation groups and our three age groups, we arrive at 18 occupation-age categories and finally compute the plant-level employment for each category.

Our time dimension will be relative time to the adoption event taking place in t_0. We split the treatment group into four groups mirroring the four possible years of robot adoption (2015−2018). The control group consists of plants that had no robots in 2014 and did not install robots later on. We split the control group randomly into four equally sized groups and assign each of these groups to one of the treatment groups. The relative time for the control group is defined to be the same as that of the treatment group the control group is randomly assigned to. We follow each plant from three years before adoption to the latest post-adoption year observed. In this way, we can observe pre-adoption trends and post-adoption outcomes. We only consider plants observed in all the years from $t_0 - 3$ to $t_0 + 1$.[22] Overall we have linked data for 116 robot-adopting manufacturing plants: 24 plants adopted robots in 2015, 27 plants in 2016, 21 plants in 2017, and 44 plants in 2018.

Table 4.1 presents basic summary statistics measured in the base year. In line with prior research, we confirm that robot adopters are initially larger and employ a higher fraction of simple manual occupations; i.e. occupations having the highest potential for getting replaced by robots. We additionally show that the initial age structure of adopters closely resembles that of non-users. Interestingly, the higher incidence of

[22] Ideally, one would examine the employment effect of robot adoption over a longer time horizon to include more post-adoption periods. However, for plants that adopted robots in 2018 (amounting to more than one-third of all adopters), the year $t_0 + 2$ would already hit the period of Covid-19. There is thus a tradeoff between the window length of the event study and the number of adopters included in the sample. We also rerun our main specifications including the year $t_0 + 2$ and using a reduced sample that excludes plants which adopted robots in 2018 and the corresponding control group. We still find an increase in employment and churning as well as a more positive employment development for non-routine occupations and younger workers. Results are available upon request.

Table 4.1: Summary Statistics

	Robot Adopter (N=116)				Non-User (N=1962)			
	mean	std dev	median	change	mean	std dev	median	change
Employment	221	251	140	16	86	177	30	3
Hires	24	35	14	3	11	25	4	0
Separations	21	23	14	4	9	17	4	3
Occupation Structure (%)								
Simple manual	34	23	32	0	25	26	16	0
Qualified manual	29	22	27	-1	30	27	22	-1
Technician/engineer	12	9	11	1	13	16	8	0
Manager	3	3	2	0	3	5	0	0
Service	9	9	7	1	10	14	6	0
Admin	13	10	10	0	19	17	14	0
Age Profile (%)								
Young (20−34)	26	11	25	0	25	14	24	-2
Mid-age (35−54)	50	11	50	-4	50	14	50	-3
Old (55−65)	20	8	18	3	20	12	19	4

Notes: (i) Based on BHP data we report the plant-level summary statistics for the manufacturing sample. (ii) For robot adopters and non-users, we report separately the mean, standard deviation ("std dev"), and median for the base year $t_0 - 3$. We also report the average change from $t_0 - 3$ to $t_0 + 1$ (Column "change"). (iii) Employment, hires, and separations are reported in levels, whereas all other variables are reported as percentage shares of the *total* employment. (iv) Age shares do not add up to 100% as we exclude workers younger than 20 years old.

simple manual occupations in adopting plants holds within all age groups.[23] Overall, initial differences between the two groups of plants are more related to occupations than to age.

Our fourth data set is the German qualification and career survey (QAC), which is a large worker survey conducted every six or seven years by the Federal Institute for Vocational Education and Training (BIBB) in cooperation with the Federal Institute for Occupational Safety and Health (BAuA).[24] The data contains very detailed information on tasks performed, worker occupation, age, and sector alongside standard worker demographics. Based on the 2012 wave of the QAC we calculate the share of replaceable tasks with respect to occupation, age, and occupation × age group. Importantly, the QAC is not allowing us to trace within-firm or within-worker changes in tasks.

23 For further summary statistics by occupation and age, see Table A4.3 in the Appendix.

24 See Rohrbach-Schmidt and Hall (2013) for a description of the data. An alternative source for the occupation-level task information is the expert database Berufenet. We stick to the QAC data because we find the plant-level routine task intensity (converted from occupation level through plant-level occupation composition) based on the QAC data has the strongest predictive power about robot adoption.

4.3.2 Empirical Approach

There is a recent econometric literature challenging commonly applied extensions of the standard two-period difference-in-differences (DiD) model to settings where, as in our study, units are treated at different points in time. In particular, Goodman-Bacon (2021) splits up the commonly applied extended DiD model of the form $Y_{it} = \alpha + T_t + \beta^{DiD} D_{it} + \epsilon$ into the various standard two-period DiD comparisons that the extended model implicitly is comprised of. He points out that comparisons where previously treated units serve as control for later treated units can yield misleading DiD coefficients.[25] To avoid any such misleading comparisons, we analyze the consequences of robot adoption within a parsimonious event-study design taking into account the staggered implementation of robots. As we explained in section 4.3.1, we essentially split up our sample into four standard DiD models (i.e. one for each of the four robot adoption years) where we randomly assign to each treatment cohort a control group of firms never adopting robots. The final regression recombines those four DiD models within a standard event-study framework in relative time. Restructuring the data in *relative time to the event* assures making only meaningful treatment-control comparisons.

The estimation equation

$$Y_{it} = \alpha_i + \sum_{k=-2}^{1} \beta_k \, T_t^k + \sum_{k=-2}^{1} \gamma_k \; Robot_i \, T_t^k + \epsilon_{it}, \tag{4.1}$$

relates plant i's outcome variable of interest Y_{it} in relative time t to the event of robot adoption. As described above, outcome variables are total employment and the number of employees in certain occupational categories, age categories, and interactions of occupation and age. To analyze worker flows directly, we additionally analyze the number of hires and separations of all employees and within occupational and age categories. We control for an individual fixed effect α_i for each plant i. T_t^k is a

[25] Callaway and Sant'Anna (2021) make a closely related point and extend it to an event-study setting with leads and lags.

relative time dummy that equals one if $t = k$. The coefficient vector β_k measures the development of Y_{it} over relative time in the control group. $Robot_i$ is the time-invariant treatment group dummy for robot adopters and we interact it with relative time T_t^k. The coefficient of the interaction effect, γ_k, is our main coefficient of interest. It measures the development of Y_{it} in the treatment group relative to the control group. We will use γ_k to discuss the effects of robot adoption as well as potential pre-trends in our dependent variables. Finally, ϵ_{it} is an idiosyncratic error term. Remember that we exclude plants that already used robots in the initial year 2014 because they do not have a robot adoption decision to make.[26]

Our event-study specification is closely related to the setup in Cengiz et al. (2019) who study how state-level minimum wage changes affect low-wage jobs. In particular, they select for each event (a minimum wage increase) only "clean" control states that do not experience any nontrivial minimum wage increases during the event window, avoiding potentially misleading comparisons between the already-treated and the later-treated states. Our specification follows the same spirit of finding a clean control group for each adopter group.[27] Deshpande and Li (2019) and Fadlon and Nielsen (2019) adopt similar ideas for the staggered DiD designs but their sample construction exploits the randomness of the event timing. Moreover, as a robustness check, we also follow Sun and Abraham (2021) and adopt a staggered DiD design that does not require splitting the comparison group. Our main findings are robust to this alternative estimation approach (Appendix Table A4.7).

Although our event study setting takes into account time-invariant differences between adopters and non-adopters and allows checking for pre-trends, it can not dispel all endogeneity concerns. For instance, a positive product demand shock may induce firms to adopt robots and hire workers. However, utilizing a survey question on whether plants expect sales growth in the following year shows that 2018 robot

[26] We also consider a robustness check that includes in the treatment group both the first-time robot adopters and incumbent users in 2014 which experienced a spike in robot use (a 40% increase over two consecutive years) from 2014 to 2018. Our main findings are qualitatively robust in this alternative specification and the results are available upon request.

[27] This idea of finding a clean control has been formally studied in Dube et al. (2023). We thank one of our referees for pointing out this connection.

adopters are not more likely to expect sales growth from 2017 to 2018 than plants in the control group. As first-time robot adoption incurs a material reorganization of production processes and, hence, requires a substantial amount of planning, we consider it unlikely that robots are introduced as a response to an *unexpected* demand shock. Our result on rising worker churning will also make clear that a simple demand shock story cannot explain the data. More importantly, our paper is primarily about workforce *composition* and not about total employment. We would like to understand which types of workers are hired or displaced when robots are introduced. Our choice of a homothetic production function in section 4.2 already highlights that we do not think of a demand shock as potentially altering workforce composition and rather argue that we can learn important lessons about substitutability and complementarity from observing which types of workers come and go upon robot adoption. Finally, robot adopters may poach workers from non-adopters and thus create spillovers to the control group potentially biasing our results. We do not think that this is a major concern in our case as the number of adopters is very small compared to the number of non-adopters and, hence, any spillover effects will be small, too. What is more, Aghion et al. (2023) show that business stealing effects are less of a concern in sectors that face international competition. Manufacturing sectors as studied in our paper clearly belong to this group.

To reduce the influence of potential outliers and to normalize estimated effects to a common metric when the units of observation are of different (plant) size, a logarithmic transformation of the dependent variable is commonly applied by researchers. However, our data contains zero-valued dependent variables, and taking logs would lead to a loss of observations. To deal with this, we use an inverse hyperbolic sine (IHS) transformation.[28] Coefficients can be interpreted similarly to those from standard log-linear models. Following suggestions made in Mullahy and Norton (2022) and Chen and Roth (2024), we show IHS robustness using alternative outlier-robust transformations and specific tests for intensive and extensive margin effects in Appendix A4.3.

[28] The IHS of a variable z is simply given by $\ln(z + \sqrt{z^2 + 1})$. See Burbidge et al. (1988) or MacKinnon and Magee (1990).

4.4 Results

4.4.1 Tasks, Occupations, and Age

We start by showing the routine task content of work by occupation and age in the German manufacturing sector. We classify worker tasks into manual routine tasks and non-routine tasks following the framework outlined in D. H. Autor et al. (2003) and Spitz-Oener (2006). Essentially we assign tasks from the QAC data to these categories and compute within the manufacturing sector a worker-level task index taking into account also the frequency with which workers perform the respective task. For each worker we weight each task with the frequency of task performance (often = 1, sometimes = 0.5, rarely/never = 0) and then calculate the share of manual routine tasks (manufacturing and producing goods; monitoring and control of machines; transporting and storing) out of all tasks performed. We aggregate the routine task content i) per occupation, ii) per age group, and iii) at occupation×worker age cells. These categories mimic the categories we use in the event study regressions.

Table 4.2 reports the routine task content by occupation and age for the manufacturing sector. A first important result is that occupations differ markedly in their routine task content. Simple manual occupations show the highest routine task content. These are occupations that in most cases do not require formal vocational training. On the other end of the spectrum, we find high-skill occupations including managers and technicians/engineers. This supports the key assumption in our theoretical framework that the task content of jobs (replaceability) varies by occupation. We thus expect the displacement effect of robots to vary substantially by occupation and being lowest for managers and technicians/engineers. We also present results for service and administrative occupations. These are back-office occupations, for instance, accountants or security officers, and we would not expect to see any direct displacement effect coming from robots. This implies that the routine task content of those occupations should not predict employment outcomes. However, if the productivity effect is strong enough, we expect a slight increase in employment for those occupations.

A striking new result is that the routine task content of work does not have an age bias. Overall, but also within each of the occupation groups, the routine task content does not vary with age. Also, Panel B of Table 4.2 confirms that workers of different ages overall do not sort systematically into occupations with different routine task content.[29] Based on these empirical facts, task-based models (including our own) predict that the displacement effect of robots is age-neutral. Taken together the key result of our descriptive analysis of the task content of occupations and age groups is that the displacement effect of robots will vary along the occupational dimension of work but not along the age dimension.

Table 4.2: Replaceability of Tasks by Occupation and Age (%)

	Occupation						
Age	simple manual	qualified manual	techn. engin.	manager	service	admin	overall
PANEL A: Share of Replaceable Tasks by Occupation and Age (%)							
Young (20−34)	28.82	22.19	10.67	9.80	20.80	9.19	19.11
Mid-age (35−54)	27.54	21.98	11.84	10.22	25.27	9.21	19.05
Old (55−65)	28.85	22.05	10.66	12.81	25.44	8.77	18.72
Overall	27.99	22.04	11.40	10.49	24.47	9.11	19.01
PANEL B: Age Distribution by Occupation (%)							
Young (20−34)	20.25	25.72	21.85	20.79	16.90	19.91	21.82
Mid-age (35−54)	64.17	55.44	62.57	65.39	59.07	57.43	60.23
Old (55−65)	15.58	18.83	15.58	13.82	24.03	22.66	17.95

Notes: (i) The calculations are based on the manufacturing sample of the BIBB/BAuA data (2012 wave). (ii) Panel A displays the average ratio (%) of the three tasks that are potentially replaceable by robots (manufacturing and producing goods; transporting and storing; monitoring, control of technical processes) to the total number of tasks performed. (iii) The counting of tasks is adjusted to the frequency of task performance (often = 1, sometimes = 0.5, rarely/never = 0). (iv) Panel B displays the age profile of employees across occupations. (v) $N = 2,921$ and sampling weights are applied.

[29] Middle-aged workers are slightly overrepresented in simple manual tasks, which is in line with US evidence presented in Acemoglu and Restrepo (2022). However, this overrepresentation (64% share in simple manual occupations compared to an overall share of middle aged workers of 60%) is small enough to let us conclude that there is no systematical sorting in our German data.

4.4.2 Employment and Worker Turnover

The first implications of the model outlined in section 4.2 are i) that the employment effect is ambiguous and ii) that, if it is positive, it is accompanied by increased worker reallocation. In our empirical test, we will directly look at these margins by analyzing total employment, total hires, and total separations.

Our event study results are presented in Table 4.3. As discussed in the previous section, we use the IHS transformation yielding approximately a coefficient interpretation as in a log-linear model.[30] Column 1 shows that total employment increases in the robot adoption year by about 5 percent compared to the control group. This effect remains stable in the year after adoption. We do not see a statistically significant pre-trend.

Hiring, as reported in column 2, shows a pronounced spike in the robot adoption year: we see an increase of 24 percent compared to the base year and this effect is highly statistically significant.[31] We find some weak evidence that hiring increased already before robot adoption and strong evidence that excess hiring remains in the post-adoption period. We conclude that robot adoption triggers excess hiring and that excess hiring happens mostly in a time span from one year before to one year after adoption. Distributing hiring over time is rational when firms face convex hiring costs.[32]

Column 3 shows our results for separations. We find an increase in separations in the post-adoption period. Separation rates are also somewhat higher before and upon adoption but the effect is relatively small and not statistically significant. Hence, overall we find evidence for excess separations being smaller in magnitude than excess hiring, which leads to an overall increase in employment. In light of the model, we conclude that the degree of complementary between labor and robots is high enough

[30] This approximation can be inaccurate for values smaller than 10 (Bellemare and Wichman, 2020). For respective cases, we use the exact transformation before interpreting estimation coefficients.

[31] In the base year, robot adopters hire on average 24 employees so the 24% increase corresponds to an increase in hiring by approximately 6 employees in the year of adoption.

[32] We arrive at qualitatively similar results when we do not use the IHS transformation and compute semi-elasticities at the sample means of the dependent variable.

Table 4.3: Employment and Worker Flows

	(1) Employment	(2) Hires	(3) Separations
t−2	0.0009	-0.0636***	0.0539***
	(0.0040)	(0.0184)	(0.0193)
t−1	0.0091*	-0.0418**	0.0425**
	(0.0052)	(0.0192)	(0.0202)
t	0.0152**	0.0126	0.0938***
	(0.0068)	(0.0205)	(0.0199)
t+1	0.0141*	0.0029	0.1211***
	(0.0085)	(0.0214)	(0.0208)
t−2 × Robot	0.0141	0.0430	-0.0214
	(0.0103)	(0.0715)	(0.0623)
t−1 × Robot	0.0204	0.0918	0.0708
	(0.0153)	(0.0762)	(0.0614)
t × Robot	0.0477**	0.2442***	0.0503
	(0.0233)	(0.0757)	(0.0673)
t+1 × Robot	0.0511*	0.1705**	0.1168*
	(0.0281)	(0.0797)	(0.0705)
Within R^2	0.0029	0.0050	0.0075

Notes: (i) This table reports the event-study results based on Equation (5.1). The number of observations is 10390 across all columns. (ii) The plant fixed effect is included. (iii) The dependent variables are plant-level employment, number of new hires, and number of separations. They are based on the BHP data and rescaled by the inverse hyperbolic sine transformation. (iv) Standard errors in parenthesis are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

to sustain positive employment effects. As predicted by the model, worker reallocation increases when robots are introduced and the productivity effect is strong.[33]

Table A4.1 shows that these results are robust to modifications in the sample and the transformation of the dependent variable. Panel A in Table A4.1 shows that excluding plants having less than 20 employees does not change any of the results despite reducing the number of observations by about one third. Panel B shows results from a percentile regression where we use the percentile rank of the dependent variable by relative time instead of IHS.[34] We again find that the employment percentile rank rises at robot adoption as do hirings. We also confirm that hiring and separations

33 Battisti et al. (2023) also find increased worker turnover when analyzing broadly defined organizational and technological changes at the plant level.

34 See D. Autor et al. (2022) for a similar approach to scrutinize the robustness of IHS results.

remain high in the year after robot adoption. Panel C in Table A4.1 uses the standard logarithmic transformation of the dependent variable instead of IHS and shows very similar results. Finally, Panel D confirms main results when applying a model in levels where the dependent variable is expressed as a share of base-year plant size.

4.4.3 Occupational Groups

Column 1 of Table 4.4 shows zero employment effects for simple manual workers. The effect for qualified manual workers (column 2) is noisily estimated but implies an employment increase of about 6 percent. Importantly, columns 3 and 4 show strong positive employment effects for technicians/engineers and managers. We alternatively group workers based on the binary occupation-level replaceability measure from Graetz and Michaels (2018).[35] Confirming our main results, Appendix Table A4.4 shows a sizable increase in employment of non-replaceable occupations and no discernible change in employment of replaceable occupations. Hence, our results confirm the predictions of our task-based model that the displacement effect is occupation-specific and tends to be smaller for occupations performing less routine (or less replaceable) tasks. Finding the least favorable employment effects for simple manual workers confirms Acemoglu et al. (2020) who document a negative association between robots and the share of production workers in employment together with an increase in overall employment.[36]

Appendix Table A4.5 shows how hires and separations shape the employment evolution in the occupational groups. We find increased hiring across *all* occupational categories and excess separations take place more prominently among simple manual

[35] We use the Blossfeld categories as our preferred grouping because this widely used categorization for the German data makes it easier to compare our results with the findings in the literature, and more importantly, suggested by Table 4.2, occupation groups based on the Blossfeld categories differ from each other systematically in terms of replaceability.

[36] Acemoglu et al. (2020) define production workers as unskilled industrial and artisanal workers. Humlum (2021) also finds that robot adoption significantly alters the occupation composition of firms' labor demand and that production workers (mostly, line workers) experience the worst employment outcomes.

occupations, which again highlights the importance of the displacement effect for them.[37]

As we have shown an employment increase upon robot adoption, one might wonder whether robot adoption effects on the occupational composition also contain 'expansion effects' in the sense that firms may change their occupational composition when they grow irrespective of robot adoption. Reassuringly, Appendix Figure A4.2 shows that employment effects are more positive among non-routine occupations even if we restrict the sample to non-expanding plants.

Summing up, the occupational breakdown confirms the model predictions by showing that occupations performing the least (most) automatable tasks experience the strongest (weakest) gains in employment. Another interesting finding is that worker flows associated with robot introduction mostly happen in the exact year of robot adoption with no evidence for anticipation effects.

4.4.4 Worker Age

Our model implies that the impact of robot adoption on employment is more positive for younger workers as they should be able to make better use of the new tasks generated by robot adoption. This is because they find it easier or more profitable to adapt to new situations (see the discussion on age-specific adaptability in section 4.1) or because of the more recent occupational training (newer vintage of human capital). Before diving into the occupation-age nexus, we present the overall impact on the workforce age profile.

[37] Table A4.2 presents robustness checks along the same lines as those presented in the previous subsection. Excluding small firms yields quantitatively very similar results. The qualitative patterns are preserved in the percentile regressions. The log transformation of the dependent variable is also confirming the main results but a high number of zero-valued observations for some occupations leads to severe reductions in sample size.

Table 4.4: Employment by Occupation and Age

	Occupation						Age		
	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin	(7) young (20−34)	(8) mid-age (35-54)	(9) old (55−65)
t−2	0.0001	0.0031	0.0102*	0.0163***	0.0048	0.0101	-0.0074	-0.0084	0.0528***
	(0.0077)	(0.0068)	(0.0059)	(0.0055)	(0.0072)	(0.0064)	(0.0083)	(0.0054)	(0.0081)
t−1	0.0188*	0.0001	0.0344***	0.0219***	0.0174*	0.0249***	-0.0241**	-0.0173**	0.1146***
	(0.0101)	(0.0083)	(0.0079)	(0.0074)	(0.0095)	(0.0078)	(0.0107)	(0.0071)	(0.0100)
t	0.0414***	0.0072	0.0451***	0.0320***	0.0227**	0.0341***	-0.0261**	-0.0287***	0.1706***
	(0.0120)	(0.0099)	(0.0096)	(0.0087)	(0.0114)	(0.0092)	(0.0130)	(0.0087)	(0.0118)
t+1	0.0480***	0.0100	0.0509***	0.0395***	0.0234*	0.0420***	-0.0390***	-0.0538***	0.2188***
	(0.0139)	(0.0116)	(0.0113)	(0.0102)	(0.0132)	(0.0104)	(0.0149)	(0.0108)	(0.0140)
t−2 × Robot	0.0219	0.0005	0.0270	0.0243	0.0141	0.0218	0.0244	-0.0009	0.0435*
	(0.0217)	(0.0186)	(0.0197)	(0.0303)	(0.0205)	(0.0221)	(0.0191)	(0.0132)	(0.0249)
t−1 × Robot	0.0163	0.0509*	0.0012	0.0216	0.0164	-0.0139	0.0762***	0.0134	0.0206
	(0.0293)	(0.0280)	(0.0299)	(0.0360)	(0.0314)	(0.0271)	(0.0277)	(0.0210)	(0.0260)
t × Robot	-0.0001	0.0640	0.0657*	0.0793*	0.0735	0.0275	0.1161***	0.0453	0.0106
	(0.0491)	(0.0446)	(0.0358)	(0.0412)	(0.0491)	(0.0307)	(0.0355)	(0.0284)	(0.0370)
t+1 × Robot	0.0155	0.0611	0.0789**	0.1021**	0.0873	0.0301	0.1396***	0.0591*	0.0109
	(0.0577)	(0.0559)	(0.0390)	(0.0482)	(0.0545)	(0.0330)	(0.0408)	(0.0334)	(0.0411)
Within R^2	0.0050	0.0013	0.0097	0.0072	0.0027	0.0057	0.0029	0.0076	0.0745

Notes: (i) This table reports the event-study results based on Equation (5.1). The number of observations is 10390 across all columns. (ii) The plant fixed effect is included. (iii) The dependent variables are plant-level employment in each of the six Blossfeld occupation groups and the three age groups. They are based on the BHP data and rescaled by the inverse hyperbolic sine transformation. (iv) Standard errors in parenthesis are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column 7 of Table 4.4 shows that the partial effect of robot adoption on young workers' employment is 11 percent around adoption and further increases to 13 percent one year after adoption.[38] The employment of young workers has been increasing already before robot adoption, which is however partly driven by a decline in the control group.

We find small and marginally significant increases in employment for middle-aged and no effect for older workers.[39] Appendix Table A4.6 shows a spike in hires of young workers exactly around robot adoption thereby confirming that the increase in young workers is (at least partly) triggered by robot adoption. When looking at the age composition of new hires we find a larger share of young workers and a smaller share of older workers in robot adopting plants. As Appendix Figure A4.2 shows the same strong relative increase in the employment of young workers even in a sample of non-expanding firms, we conclude that the change in the age profile upon robot adoption is unlikely being driven by firm expansion *per se*. The increase in young worker hires confirms results in Aubert et al. (2006) who analyze technology adoption at the firm level. Appendix Table A4.6 additionally shows an increased separation rate for older workers being in line with the results in Bartel and Sicherman (1993). Battisti et al. (2023) also report a decline in the employment share of older workers following broadly defined organizational and technological changes at the plant level.

We argued before that negative effects on young workers' employment at the aggregate level as reported in Acemoglu and Restrepo (2022) and Dauth et al. (2021) are not necessarily a sign of young workers being substitutes for robots as the employment decline might be driven by non-adopters. Column 7 of Table 4.4 directly supports this notion by showing that the employment of young workers decreases in the control group.

[38] To facilitate a comparison of the main results, we collect the point estimates for the year of robot adoption (γ_0) in Tables 4.3 and 4.4 and present them in Appendix Figure **??**.

[39] These results are confirmed by robustness checks in Appendix Table A4.2.

Acemoglu and Restrepo (2022) argue that younger workers are more likely to be displaced by robots. Our results in Table 4.2, however, imply that the displacement effect has no age bias. From this evidence and our theoretical discussion we concluded that the age effect will have more to do with the reinstatement effect of robots. An interesting question is whether, in contrast to Germany, the routine task intensity does have an age bias in the US. While we can not test this on our own, we think there are good reasons to believe that Germany and the US differ in that respect because of the marked differences in the vocational education training (VET) system. Young production workers in Germany usually undergo a formal and sophisticated three-year VET (Acemoglu and Pischke, 1998), which arguably enables them to take over quite complex tasks already when they start their professional careers. The US does not

Table 4.5: Young Employees (20−34 years old) by Occupation

	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin
t−2	-0.0050	-0.0013	0.0003	0.0017	-0.0033	0.0022
	(0.0092)	(0.0086)	(0.0075)	(0.0055)	(0.0077)	(0.0089)
t−1	0.0059	-0.0236**	0.0231**	-0.0008	0.0013	-0.0064
	(0.0114)	(0.0108)	(0.0098)	(0.0070)	(0.0103)	(0.0113)
t	0.0163	-0.0267**	0.0355***	0.0046	0.0007	-0.0100
	(0.0137)	(0.0131)	(0.0114)	(0.0081)	(0.0115)	(0.0126)
t+1	0.0146	-0.0246*	0.0346***	0.0006	0.0089	-0.0224
	(0.0153)	(0.0145)	(0.0133)	(0.0092)	(0.0127)	(0.0141)
t−2 × Robot	0.0646*	-0.0219	0.0547	-0.0248	0.0370	0.0269
	(0.0382)	(0.0286)	(0.0339)	(0.0393)	(0.0395)	(0.0427)
t−1 × Robot	0.0885*	0.0359	0.0166	-0.0769*	0.0979*	0.0401
	(0.0504)	(0.0416)	(0.0434)	(0.0459)	(0.0501)	(0.0484)
t × Robot	0.1281**	0.0790	0.0995*	-0.0914*	0.0973	0.1314**
	(0.0619)	(0.0558)	(0.0541)	(0.0539)	(0.0608)	(0.0524)
t+1 × Robot	0.1377*	0.1030	0.0761	-0.0355	0.1134	0.0737
	(0.0724)	(0.0703)	(0.0657)	(0.0568)	(0.0691)	(0.0550)
Within R^2	0.0022	0.0022	0.0047	0.0016	0.0017	0.0017

Notes: (i) This table reports the event-study results based on Equation (5.1). The number of observations is 10390 across all columns. (ii) The plant fixed effect is included. (iii) The dependent variables are plant-level employment of young workers (20–34 years old) in each of the six Blossfeld occupation groups. They are based on the BeH data and rescaled by the inverse hyperbolic sine transformation. (iv) Standard errors in parenthesis are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

have a large-scale similarly sophisticated VET system implying learning by doing on the job. Hence, it is plausible that young production workers in the US will perform rather simple routine tasks when starting their careers and will take over more complex tasks as soon as they have gathered the required knowledge and experience.

4.4.5 Occupation by Worker Age

According to our model, the effect of robots on the occupation × age profile hinges on the two margins of adjustment in task requirement: initial task specialization and new task adaptation. As we showed that initial task specialization is found age-neutral even within occupations, new task adaption will be key. Tables 4.5 to 4.7 show results for occupation × age cells. As these cells can get quite small, we restrict ourselves to a

Table 4.6: Middle-aged Employees (35−54 years old) by Occupation

	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin
t−2	-0.0188**	-0.0100	0.0051	0.0130**	-0.0030	-0.0008
	(0.0074)	(0.0075)	(0.0065)	(0.0056)	(0.0075)	(0.0074)
t−1	-0.0238**	-0.0111	0.0016	0.0093	-0.0080	0.0079
	(0.0102)	(0.0096)	(0.0086)	(0.0079)	(0.0099)	(0.0095)
t	-0.0084	-0.0293***	-0.0065	0.0136	-0.0140	0.0026
	(0.0120)	(0.0111)	(0.0104)	(0.0096)	(0.0117)	(0.0114)
t+1	-0.0128	-0.0409***	-0.0207*	0.0126	-0.0302**	-0.0159
	(0.0141)	(0.0128)	(0.0118)	(0.0113)	(0.0131)	(0.0130)
t−2 × Robot	0.0118	0.0192	0.0041	-0.0370	-0.0328*	0.0090
	(0.0227)	(0.0250)	(0.0256)	(0.0288)	(0.0194)	(0.0296)
t−1 × Robot	0.0118	0.0372	0.0393	-0.0120	-0.0511	-0.0125
	(0.0354)	(0.0383)	(0.0316)	(0.0391)	(0.0366)	(0.0398)
t × Robot	-0.0033	0.0866	0.1154***	0.0284	0.0265	0.0072
	(0.0528)	(0.0561)	(0.0387)	(0.0455)	(0.0500)	(0.0466)
t+1 × Robot	0.0121	0.0472	0.1078**	0.0193	-0.0024	0.0773
	(0.0579)	(0.0627)	(0.0478)	(0.0505)	(0.0585)	(0.0534)
Within R^2	0.0008	0.0033	0.0030	0.0011	0.0019	0.0013

Notes: (i) This table reports the event-study results based on Equation (5.1). The number of observations is 10390 across all columns. (ii) The plant fixed effect is included. (iii) The dependent variables are plant-level employment of middle-aged workers (35–54 years old) in each of the six Blossfeld occupation groups. They are based on the BeH data and rescaled by the inverse hyperbolic sine transformation. (iv) Standard errors in parenthesis are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

discussion of the broader patterns instead of discussing the magnitudes of single point estimates.

Table 4.5 shows our event study results for young workers. Among young workers, all occupations except managers *benefit* from robot adoption. Analogously, Table 4.6 reports result for middle-aged workers. In this age group, technicians and engineers stand out as the group that benefits the most. Among older workers (Table 4.7) the number of managers rises the most. Here we again find a strong pre-trend suggesting that the stock of senior managers has been built up over a longer time span. We conclude that young workers' employment rises across all occupational groups except for young managers (which is an extremely small group) and that organizing the change of production towards robotics seems to require experienced managers.

Table 4.7: Old Employees (55−65 years old) by Occupation

	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin
t−2	0.0415***	0.0417***	0.0266***	0.0097*	0.0183**	0.0314***
	(0.0079)	(0.0078)	(0.0064)	(0.0053)	(0.0078)	(0.0077)
t−1	0.0770***	0.0701***	0.0627***	0.0266***	0.0360***	0.0646***
	(0.0101)	(0.0100)	(0.0085)	(0.0072)	(0.0104)	(0.0100)
t	0.1081***	0.1076***	0.0910***	0.0335***	0.0570***	0.1120***
	(0.0118)	(0.0118)	(0.0104)	(0.0085)	(0.0120)	(0.0121)
t+1	0.1509***	0.1297***	0.1248***	0.0444***	0.0753***	0.1544***
	(0.0135)	(0.0138)	(0.0125)	(0.0102)	(0.0136)	(0.0137)
t−2 × Robot	0.0252	0.0310	0.0042	0.0772**	0.0026	0.0200
	(0.0257)	(0.0309)	(0.0297)	(0.0314)	(0.0329)	(0.0298)
t−1 × Robot	0.0729**	0.0640	-0.0331	0.0760*	-0.0002	0.0426
	(0.0358)	(0.0398)	(0.0366)	(0.0455)	(0.0470)	(0.0360)
t × Robot	0.0568	0.0865	0.0157	0.1212**	0.0527	0.0424
	(0.0477)	(0.0598)	(0.0435)	(0.0497)	(0.0609)	(0.0436)
t+1 × Robot	0.0584	0.0981	0.0164	0.1449***	0.0358	-0.0118
	(0.0516)	(0.0681)	(0.0520)	(0.0548)	(0.0669)	(0.0577)
Within R^2	0.0366	0.0290	0.0313	0.0104	0.0094	0.0367

Notes: (i) This table reports the event-study results based on Equation (5.1). The number of observations is 10390 across all columns. (ii) The plant fixed effect is included. (iii) The dependent variables are plant-level employment of old workers (55–65 years old) in each of the six Blossfeld occupation groups. They are based on the BeH data and rescaled by the inverse hyperbolic sine transformation. (iv) Standard errors in parenthesis are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.5 Conclusion

We analyze novel and rich plant-level data on robot adoption to understand the employment impact of robotization. Our analysis allows observing the technological relationships between robots and various types of human labor directly in the production units. The degrees of substitution and complementarity between robots and heterogeneous labor measured with aggregate data (e.g. using industry variation in robot exposure at the local labor market level) will include competitive reactions of employers not using robots and, thus, do not necessarily reflect the true micro-level mechanisms.

We combine plant-level data on robot use with administrative data on workers employed in those plants and also data on the task content of jobs. This allows us to scrutinize at a very granular level which occupational groups, which age groups, and which age groups within occupational groups are complements or substitutes to robot adoption and how this relates to the task content of jobs. We structure the analysis by setting up a partial equilibrium model of robot adoption with heterogeneous labor. The task-based model predicts that non-routine task intensive occupations and workers who can better adapt to new tasks are more likely to gain from plant-level robotization. Our study is among the first production-unit studies on robots testing the main predictions of task-based models, i.e. more positive employment effects for occupations performing less routine manual tasks. We are first analyzing the age effects of robots using micro data.

We show descriptively that task replaceability varies primarily with occupation but barely with age implying that the displacement effect of robots should be occupation-biased but age neutral. In line with the predictions of our model, robot adoption is accompanied by rising employment (+5 percent) coupled with strongly increased hiring and modestly increased separations in particular for the most routine task intensive occupations. We do not find negative employment effects for any of the subgroups analyzed. Employment gains are concentrated among younger workers and the least routine-intensive occupations, i.e. technicians/engineers and managers. The occupation-specific results thus directly confirm predictions of the widely used task-based framework. The more positive effects for younger workers mainly point to their greater adaptability to new tasks as predicted by cognitive science literature and human capital theory and demonstrated in earlier empirical papers on technology adoption (e.g. Aubert et al., 2006). As we find that routine task intensity varies with occupation but not with age, the displacement effect will have no age bias but will be occupation-dependent. Through the lens of our model and the concepts of displacement and reinstatement effects theorized by Acemoglu and Restrepo (2018), our results thus imply that the displacement effect of robots is primarily occupation-dependent (i.e. task-dependent) and age-neutral whereas the reinstatement effect (or "new task channel") mostly depends on workers' age.

We conclude that micro-level evidence is important to understand which groups of workers are complements or substitutes for robots in production. The emerging picture is nuanced: we verify that routine-task-performing occupations are indeed relative substitutes to robots at the production-unit level and that young workers have an advantage in using the chances of new technology. Our results imply that a shortage of young workers in low- and middle-skilled occupations will hinder the large-scale adoption of robot technology. They also imply that older workers in those occupations will see their relative demand decline. Accelerated adoption of robot technology may therefore not only increase the demand for robot-complementary occupations but also contribute to a divide between young and old production workers, where the former may see a rather bright future in growing high-tech plants while the latter being stuck in small low-tech companies.

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Appendix

A4.1 Formal Results and Proofs

We start with two propositions for our baseline model. The first proposition concerns the self-selection into robot adoption which is well known in the literature (Bonfiglioli et al., 2020; Koch et al., 2021). The second proposition concerns the ambiguous effect of robot adoption on overall employment.

Proposition 1. *There exists a productivity threshold $\bar{\phi}$ such that firm i adopts robots if its productivity $\phi_i > \bar{\phi}$,*

Proof. If firm i does not adopt robots, by symmetry across different tasks, its production function is simply given by $y_i = \phi_i \ell_i$, where ℓ_i is firm i's employment of human labor. Standard derivation based on the production function and the iso-elastic demand yields

$$\pi_i = \zeta \frac{(\eta - 1)^{\eta-1}}{\eta^\eta} \left(\frac{\phi_i}{w}\right)^{\eta-1},$$

where π_i is firm i's profit. If firm i adopts robots, its production function is given by

$$y_i = \phi_i \left(\theta^{\frac{1}{\sigma}} (\lambda k_i)^{\frac{\sigma-1}{\sigma}} + (1-\theta)^{\frac{1}{\sigma}} \ell_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where k_i firm i's robot input. Standard derivation yields

$$\pi_{k,i} = \zeta \frac{(\eta - 1)^{\eta-1}}{\eta^\eta} \left(\frac{\phi_i}{P_k}\right)^{\eta-1},$$

where $\pi_{k,i}$ is firm i's operating profit (excluding the fixed cost) after robot adoption and P_k is the price index given by

$$P_k \equiv (\theta(r/\lambda)^{1-\sigma} + (1-\theta)w^{1-\sigma})^{\frac{1}{1-\sigma}}. \tag{4.2}$$

Since $r < \lambda w$, $P_k < w$. Firm i adopts robots if and only if $\pi_{k,i} - F > \pi_i$, or equivalently,

$$\zeta \frac{(\eta - 1)^{\eta-1}}{\eta^\eta} \left[\left(\frac{\phi_i}{P_k}\right)^{\eta-1} - \left(\frac{\phi_i}{w}\right)^{\eta-1}\right] > F,$$

which can be further simplified as

$$\phi_i > \left(\frac{F}{\zeta}\frac{\eta^\eta}{(\eta-1)^{\eta-1}}\right)^{\frac{1}{\eta-1}} \left(P_k^{1-\eta} - w^{1-\eta}\right)^{\frac{1}{1-\eta}} \equiv \bar{\phi}.$$

Since $w > P_k$ and $\eta > 1$, we have $\bar{\phi} > 0$. Thus, we have obtained the desired conclusion. □

Proposition 2. *If $\sigma \geq \eta$, the total employment decreases following robot adoption. If $\sigma < \eta$, the effect of robot adoption on the total employment is ambiguous.*

Proof. If firm i does not adopt robots, its labor demand is given by

$$\ell_i = \zeta \left(1 - \frac{1}{\eta}\right)^\eta \phi_i^{\eta-1} w^{-\eta}.$$

If firm i adopts robots, its labor demand is given by

$$\ell_i' = \zeta \left(1 - \frac{1}{\eta}\right)^\eta (1-\theta) P_k^{\sigma-\eta} \phi_i^{\eta-1} w^{-\sigma}$$

where P_k is defined in (4.2). To see how the total employment changes, we consider

$$\frac{\ell_i'}{\ell_i} = (1-\theta)\left(\frac{P_k}{w}\right)^{\sigma-\eta}.$$

We know from the proof of Proposition 1, $P_k < w$. If $\sigma \geq \eta$, then it immediately follows from $P_k < w$ that $\ell_i' \leq (1-\theta)\ell_i < \ell_i$, implying a drop in total employment after robot adoption. However, if $\sigma < \eta$, we have $(P_k/w)^{\sigma-\eta} > 1$, and the overall employment change becomes ambiguous . To see the ambiguity, consider the limiting case of $\sigma \to 0$: $\frac{\ell_i'}{\ell_i} \to (1-\theta)\left(\frac{P_k}{w}\right)^{-\eta}$. If $(1-\theta)\left(\frac{P_k}{w}\right)^{-\eta} > 1$, then it is straightforward to show that there exists $\bar{\sigma} \in (0,\eta)$ such that for any $\sigma < \bar{\sigma}$, $\frac{\ell_i'}{\ell_i} > 1$. In words, the employment effect can be positive for a sufficiently small σ. Thus, we have obtained the desired conclusion. □

Next, we turn to the setup with the occupation dimension incorporated. Denote by $\ell_{i,o}$ firm i's employment in occupation o prior to robot adoption and by $\Delta\ell_{i,o}$ the employment change following robot adoption. The following proposition connects the occupation-level replaceability index θ_o with the relative employment change.

Proposition 3. *If* $\theta_o < \theta_{o'}$, *then* $\frac{\Delta\ell_{i,o}}{\ell_{i,o}} > \frac{\Delta\ell_{i,o'}}{\ell_{i,o'}}$.

Proof. With the occupation dimension being incorporated, if firm i does not adopt robots, its production function is given by

$$y_i = \phi_i\left(\sum_{o\in\mathcal{O}} \mu_o^{\frac{1}{\sigma}} \ell_{i,o}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

and if firm i adopts robots, its production function is given by

$$y_i = \phi_i\left(\theta^{\frac{1}{\sigma}}(\lambda k_i)^{\frac{\sigma-1}{\sigma}} + \sum_{o\in\mathcal{O}} (\mu_o(1-\theta_o))^{\frac{1}{\sigma}} \ell_{i,o}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where $\theta = \sum_{o \in \mathcal{O}} \mu_o \theta_o$. Following essentially the same argument as the proof of Proposition 2, we can show the change in the employment of occupation o is given by

$$\frac{\Delta \ell_{i,o}}{\ell_{i,o}} = (1 - \theta_o) \left(\frac{P_k}{w} \right)^{\sigma - \eta} - 1.$$

Thus, the employment change decreases with θ_o. We have obtained the desired conclusion. □

We make a simplifying assumption in the model that the wage rate is the same across occupations, but it should be noted that the proof above can be easily extended to a setting with occupation-specific wage rates. Similarly, the proof in what follows can also be extended to a setting with age-specific wage rates.

We now turn to the investigation of the reinstatement channel. Denote by ℓ_i^a firm i's employment in age group a prior to robot adoption and by $\Delta \ell_i^a$ the employment change following robot adoption.

Proposition 4. *Let $\theta^a = \theta$. If $\frac{\nu^a}{\mu^a}$ decreases with a, then $\frac{\Delta \ell_i^a}{\ell_i^a}$ also decreases with a.*

Proof. With the age dimension being incorporated, if firm i does not adopt robots, its production function is given by

$$y_i = \phi_i \left(\sum_{a \in \mathcal{A}} (\mu^a)^{\frac{1}{\sigma}} (\ell_i^a)^{\frac{\sigma - 1}{\sigma}} \right)^{\frac{\sigma}{\sigma - 1}}.$$

If firm i adopts robots, because of the introduction of new tasks, firm i's production function is given by

$$y_i = \phi_i \left(\theta^{\frac{1}{\sigma}} (\lambda k_i)^{\frac{\sigma - 1}{\sigma}} + \sum_{a \in \mathcal{A}} (\mu^a (1 - \theta) + \nu^a)^{\frac{1}{\sigma}} (\ell_i^a)^{\frac{\sigma - 1}{\sigma}} \right)^{\frac{\sigma}{\sigma - 1}},$$

where we assume based on the empirical evidence that the replaceability θ does not vary with age. The price index of the input bundle under robot adoption is now given by

$$P_k' \equiv (\theta (r/\lambda)^{1-\sigma} + (1 - \theta + \delta) w^{1-\sigma})^{\frac{1}{1-\sigma}}.$$

Similarly, we can derive the change in the employment of age group a as

$$\frac{\Delta \ell_i^a}{\ell_i^a} = \left(1 - \theta + \frac{\nu^a}{\mu^a}\right)\left(\frac{P_k'}{w}\right)^{\sigma-\eta} - 1,$$

which increases with $\frac{\nu^a}{\mu^a}$. If $\frac{\nu^a}{\mu^a}$ decreases with a, then $\frac{\Delta \ell_i^a}{\ell_i^a}$ must also decrease with a. Thus, we have obtained the desired conclusion. $\square$

Last, we present a result that directly follows from Proposition 4 for the setting with both age and occupation dimensions. Denote by $\ell_{i,o}^a$ firm i's employment in a and o prior to robot adoption and by $\Delta \ell_{i,o}^a$ the employment change following robot adoption. The following proposition concerns the employment effect of robot adoption in the presence of occupation-specific age bias in adaptability.

Proposition 5. *Let* $\theta_o^a = \theta_o$. *If* $\frac{\nu_o^a}{\mu_o^a} > \frac{\nu_o^{a'}}{\mu_o^{a'}}$, *then* $\frac{\Delta \ell_{i,o}^a}{\ell_{i,o}^a} > \frac{\Delta \ell_{i,o}^{a'}}{\ell_{i,o}^{a'}}$.

A4.2 Survey Questions

We provide below a word-to-word English translation of the section on robot use in the 2019 IAB Establishment Survey.

Question 77.

a) Have you used robots over the last 5 years for operational performance or production? [*A robot is any automated machine with multiple axes or directions of movement, programmed to perform specific tasks (partially) without human intervention. This includes industrial robots but also service robots. This excludes machine tools, e.g. CNC-machines.*] Yes/No.

If so:

b) How many robots have you used in total in each of the last five years? An estimation will suffice. If more robots are used in one robot cell, please count them individually. An estimation will suffice. [Interviewer: If "none" enter "0". Please enter "XXXX" if there is no information possible to single years.]

If in 2018 no use of any robot or no information possible, go to question 81. If there was use of at least one robot in 2018, go to question 78.

Question 78.

If there was use of at least one robot in 2018: How many of the robots used in 2018 were purchased at a price of less than 50,000 Euros? Please – if possible – consider only the purchase price, without any further costs for tools or the integration of the robots into your production circle.

Question 79.

How many of the robots used in 2018 are separated from employees during the regular operations with the help of a protection device, e.g. cage, fence, separate room, light barrier or sensor mat?

Question 80.

How many of the robots used in 2018 did you just purchase in 2018?

A4.3 Robustness of the IHS transformation

We aim to estimate semi-elasticities as opposed to linear effects mainly because our units of observations are of different (plant) sizes, which creates the need to normalize effects by size. For instance, robot adoption may trigger a higher absolute number of additional hires and separations in larger plants as opposed to small plants simply because of the different plant sizes. Taking logs solves this problem by transforming effects into relative changes. A problem arises when the dependent variable sometimes contains zeros. To not lose these observations when taking logs, we opt for analyzing the inverse hyperbolic sine function (IHS) of the dependent variable. The IHS shares many features with a standard log-linear regression analysis, in particular, it allows for an approximate semi-elasticity interpretation.

Several papers used this method before but very recently, econometricians pointed to severe pitfalls. For instance, Mullahy and Norton (2022) argue that estimating marginal effects with IHS runs into problems when the fraction of zeros is high. Chen and Roth (2024) show that rescaling the dependent variable impacts estimates when there is an effect on the extensive margin. Although both papers do not explicitly consider settings that are complicated by differently sized units of observation, several of their proposals are attractive to us. We take account of the proposals by Mullahy and Norton (2022) and Chen and Roth (2024) and show robustness tests below where we i) reduce the fraction of zeros by excluding small firms with less than 20 employees, ii) perform percentile regressions as a more flexible version of the proposed linear probability models, iii) estimate models in levels where the dependent variable is expressed as a share of base-year plant size (re-scaled with the base year sample mean to arrive at a percent change interpretation), and iv) additionally show results based on standard logarithmic transformations that automatically exclude the extensive margin (i.e. observations with zeros).

We conclude that our main results are confirmed by this battery of robustness checks. In particular, employment, hiring, churning (Appendix Table A4.1), as well as the demand for non-routine tasks and young workers increase (Appendix Table A4.2).

A4.4 Additional Figures and Tables

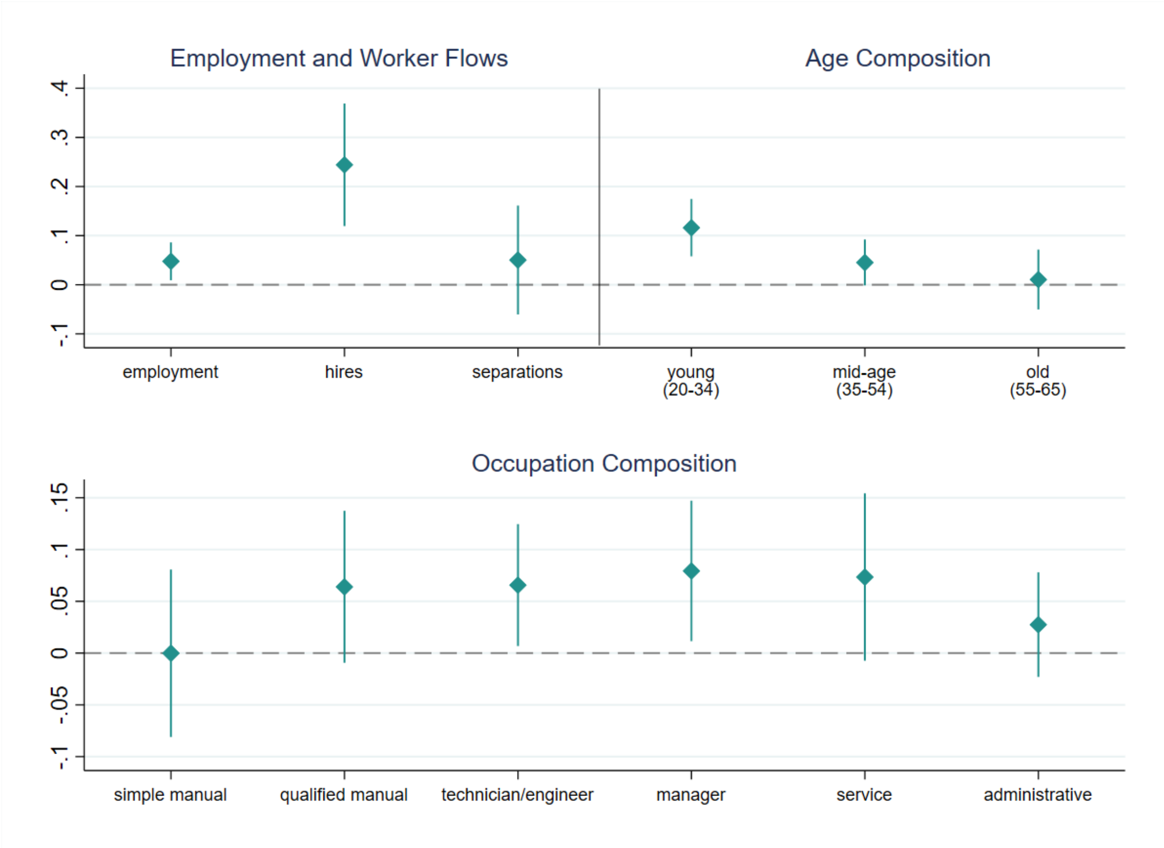

Figure A4.1: Main Results

Notes: Notes: (i) The point estimate for the effect of robot adoption in the year of adoption (γ_0) is depicted for overall employment, churning, and employment in each of the three age groups in the upper panel and employment in each of the six occupation groups in the lower panel (as reported in Tables 4.3 and 4.4). (ii) 90% confidence intervals are depicted.

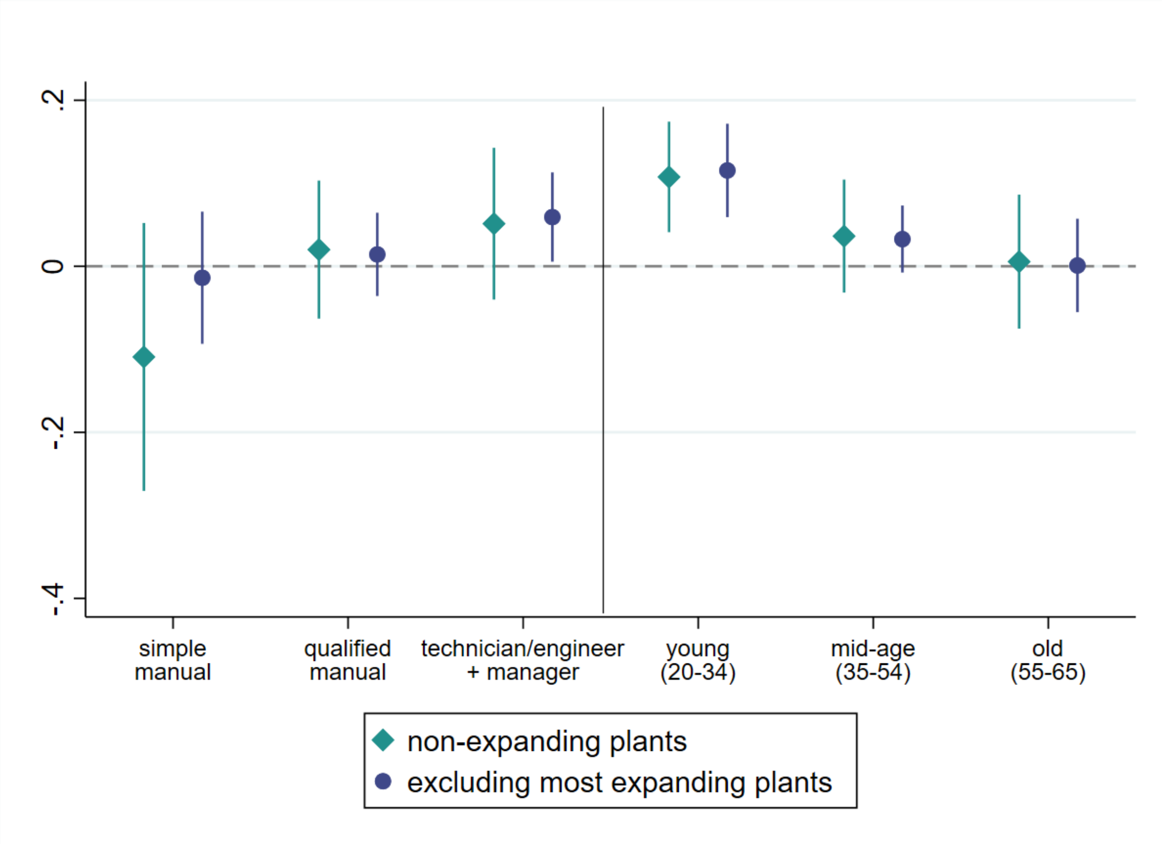

Figure A4.2: Effects on Occupation Composition and Age Profile Excluding Expanding Plants

Notes: (i) The point estimate for the employment effect of robot adoption in the year of adoption (γ_0) is depicted for three occupation groups (simple manual, qualified manual, and combined technicians/engineers/managers) and three age groups (20–34, 35–54, and 55–65) (ii) The light blue squares correspond to the sample including only non-expanding plants, whereas the blue circles correspond to the sample excluding the 10% plants with the strongest employment growth. Expansion (change in log employment) is measured between $t-2$ and t. (iii) 90% confidence intervals are depicted.

Table A4.2: Robustness Checks on IHS Transformation for Employment by Occupation and Age

	Occupation						Age		
	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin	(7) young (20−34)	(8) mid-age (35-54)	(9) old (55−65)
	PANEL A: Excluding Plants with <20 Employees ($N = 6950$)								
t−2 × Robot	0.0133	0.0148	0.0216	0.0138	0.0137	0.0071	0.0148	0.0107	0.0152
	(0.0202)	(0.0195)	(0.0210)	(0.0313)	(0.0222)	(0.0211)	(0.0195)	(0.0133)	(0.0190)
t−1 × Robot	0.0109	0.0610**	0.0086	0.0048	0.0206	-0.0293	0.0754***	0.0204	0.0007
	(0.0283)	(0.0295)	(0.0319)	(0.0363)	(0.0334)	(0.0271)	(0.0284)	(0.0193)	(0.0250)
t × Robot	-0.0030	0.0738	0.0640*	0.0748*	0.0729	0.0168	0.1140***	0.0545*	0.0005
	(0.0510)	(0.0470)	(0.0374)	(0.0414)	(0.0508)	(0.0319)	(0.0365)	(0.0280)	(0.0356)
t+1 × Robot	-0.0041	0.0918*	0.0842**	0.0906*	0.0756	0.0211	0.1359***	0.0825**	-0.0081
	(0.0565)	(0.0551)	(0.0412)	(0.0489)	(0.0572)	(0.0334)	(0.0415)	(0.0335)	(0.0378)
	PANEL B: Percentile Regressions ($N = 10390$)								
t−2 × Robot	0.4058	-0.0646	0.5886	1.3179	0.5690	0.3624	0.4619	-0.0003	0.9224**
	(0.4266)	(0.3184)	(0.4232)	(1.1142)	(0.5210)	(0.5550)	(0.3817)	(0.2730)	(0.4458)
t−1 × Robot	0.2397	0.8247*	-0.1722	1.4053	0.4477	-0.3974	0.9036*	0.1617	0.5300
	(0.5213)	(0.4995)	(0.6356)	(1.3729)	(0.7879)	(0.6424)	(0.5476)	(0.4030)	(0.5206)
t × Robot	-0.0155	0.6014	1.0668	2.4533	1.5607	0.4584	1.1822*	0.4489	0.2090
	(0.9031)	(0.7051)	(0.7484)	(1.5776)	(1.1200)	(0.7255)	(0.6771)	(0.5182)	(0.6626)
t+1 × Robot	0.1644	0.5539	1.3165*	3.5552*	1.9159	0.5356	1.3058	1.0568	0.0555
	(1.0480)	(0.9192)	(0.7833)	(1.8365)	(1.2008)	(0.7548)	(0.8016)	(0.6579)	(0.7296)
	PANEL C: Log Transformed								
t−2 × Robot	0.0003	0.0220	0.0307	-0.0265	0.0166	0.0128	0.0246	-0.0016	0.0380*
	(0.0217)	(0.0186)	(0.0230)	(0.0275)	(0.0225)	(0.0223)	(0.0196)	(0.0133)	(0.0196)
t−1 × Robot	0.0101	0.0601**	0.0048	-0.0310	0.0168	-0.0171	0.0727***	0.0171	0.0105
	(0.0295)	(0.0299)	(0.0351)	(0.0315)	(0.0286)	(0.0264)	(0.0280)	(0.0216)	(0.0255)
t × Robot	-0.0004	0.0762	0.0658	0.0328	0.0747	0.0311	0.1026***	0.0492*	0.0059
	(0.0436)	(0.0467)	(0.0404)	(0.0353)	(0.0515)	(0.0316)	(0.0357)	(0.0287)	(0.0330)
t+1 × Robot	0.0140	0.0946*	0.0686	0.0379	0.0600	0.0311	0.1132***	0.0712**	-0.0021
	(0.0492)	(0.0527)	(0.0429)	(0.0394)	(0.0582)	(0.0336)	(0.0411)	(0.0329)	(0.0350)
N	8027	8736	7723	5348	7634	9691	9716	10354	9739
	PANEL D: Level as Share of Base-year Employment ($N = 10390$)								
t−2 × Robot	0.0230	-0.0269	0.0097	0.0279	0.0267	0.0042	0.0256	-0.0045	0.0346
	(0.0188)	(0.0188)	(0.0172)	(0.0451)	(0.0247)	(0.0163)	(0.0187)	(0.0133)	(0.0239)
t−1 × Robot	0.0488*	-0.0120	-0.0294	0.0434	0.0510	-0.0095	0.0522*	0.0037	0.0147
	(0.0259)	(0.0222)	(0.0253)	(0.0634)	(0.0621)	(0.0209)	(0.0295)	(0.0209)	(0.0286)
t × Robot	0.0507	0.0216	0.0372	0.0918	0.1057	0.0045	0.1071**	0.0321	0.0163
	(0.0328)	(0.0376)	(0.0372)	(0.0791)	(0.0725)	(0.0226)	(0.0421)	(0.0274)	(0.0398)
t+1 × Robot	0.0457	0.0151	0.0422	0.0926	0.1030	-0.0025	0.1226**	0.0405	0.0106
	(0.0409)	(0.0467)	(0.0471)	(0.0919)	(0.0751)	(0.0229)	(0.0498)	(0.0321)	(0.0465)

Notes: (i) This table reports the event-study results based on Equation (5.1). (ii) The plant and relative time fixed effects are included. (iii) The dependent variables, based on BHP data, are plant-level employment in each of the six Blossfeld occupation groups and the three age groups. (iv) Panel A displays treatment effects for a sample that excludes plants with less than 20 employees, where the dependent variables are rescaled by the inverse hyperbolic sine transformation. (v) Panel B displays treatment effects for percentile regressions, where the dependent variable is measured in percentile ($0 - 100$) based on the plant-level distribution of the original outcome variable for each time period. (vi) Panel C displays treatment effects for log-transformed dependent variables. (vii) Panel D displays treatment effects for employment variables in levels as a share of base-year plant size, where estimates are re-scaled with the base year sample mean to arrive at a percent change interpretation. (viii) Standard errors in parenthesis are clustered at the plant level. (ix) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4.3: Summary Statistics: Further Details

	Robot Adopter (N=116)			Non-User (N=1962)		
	mean	std dev	median	mean	std dev	median
Hires by Occupation (%)						
Simple manual	4	5	3	4	8	0
Qualified manual	4	7	2	4	8	1
Technician/engineer	1	3	1	2	5	0
Manager	0	1	0	0	2	0
Service	1	2	0	2	5	0
Administrative	2	3	1	3	6	1
Separations by Occupation (%)						
Simple manual	4	4	3	3	7	0
Qualified manual	3	3	2	4	7	0
Technician/engineer	1	2	1	2	5	0
Manager	0	1	0	0	2	0
Service	1	2	0	1	4	0
Administrative	2	2	1	3	5	0
Hires by Age (%)						
Young (20–34)	6	5	4	6	7	4
Mid-age (35–54)	5	5	3	6	9	4
Old (55–65)	1	2	1	2	5	0
Separations by Age (%)						
Young (20–34)	5	4	4	5	7	3
Mid-age (35–54)	3	3	2	5	8	3
Old (55–65)	3	3	2	3	5	1
Occupation Structure (20–34) (%)						
Simple manual	7	8	5	6	9	2
Qualified manual	10	11	8	9	11	5
Technician/engineer	3	4	2	3	7	0
Manager	0	1	0	0	2	0
Service	1	2	1	2	4	0
Administrative	4	4	3	4	7	2
Occupation Structure (35–54) (%)						
Simple manual	17	13	15	13	15	7
Qualified manual	13	12	10	13	14	9
Technician/engineer	6	5	5	7	9	4
Manager	2	2	1	2	3	0
Service	5	6	4	5	8	2
Administrative	7	6	5	10	10	7
Occupation Structure (55–65) (%)						
Simple manual	9	8	7	6	8	2
Qualified manual	5	5	4	6	8	2
Technician/engineer	3	2	2	3	5	0
Manager	1	1	0	1	2	0
Service	3	3	2	3	5	0
Administrative	2	3	2	4	6	2

Notes: (i) Based on BHP data we report the plant-level mean, standard deviation ("std dev"), and median for the manufacturing sample in the base year $t_0 - 3$. (ii) All variables are measured as percentage shares of the *total* employment. (iii) Occupational shares do not add up to 100% as we focus on the selected Blossfeld categories, excluding very small categories such as (semi-)professions. (iv) Age shares do not add up to 100% as we exclude workers younger than 20 years old.

Table A4.4: Event Study for Replaceable and Non-Replaceable Occupations

	Graetz-Michaels Measure	
	non-replaceable	replaceable
t−2 × Robot	0.0249*	-0.0058
	(0.0150)	(0.0134)
t−1 × Robot	0.0062	0.0025
	(0.0198)	(0.0206)
t × Robot	0.0645**	0.0147
	(0.0285)	(0.0314)
t+1 × Robot	0.0779***	0.0075
	(0.0301)	(0.0404)

Notes: (i) This table reports the event-study results based on Equation (5.1). The number of observations is 10390 in both columns. (ii) The plant and relative time fixed effects are included. (iii) The dependent variables are plant-level employment in non-replaceable and replaceable occupations. The binary measure of replaceability at the occupation level is from Graetz and Michaels (2018). The employment numbers are based on the BeH data and rescaled by the inverse hyperbolic sine transformation. (iv) Standard errors in parenthesis are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4.5: Worker Flows by Occupation

	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin
			PANEL A: Hires by Occupation			
t−2	-0.0584***	-0.0413**	-0.0301**	-0.0118	-0.0147	-0.0147
	(0.0174)	(0.0178)	(0.0152)	(0.0108)	(0.0158)	(0.0168)
t−1	-0.0389**	-0.0483***	-0.0010	-0.0149	-0.0059	0.0085
	(0.0187)	(0.0179)	(0.0160)	(0.0108)	(0.0162)	(0.0169)
t	0.0185	-0.0038	0.0049	-0.0045	0.0136	0.0303*
	(0.0194)	(0.0185)	(0.0162)	(0.0110)	(0.0164)	(0.0174)
t+1	0.0351*	-0.0026	0.0043	-0.0072	0.0350**	0.0209
	(0.0199)	(0.0193)	(0.0161)	(0.0117)	(0.0176)	(0.0174)
t−2 × Robot	0.0096	-0.0311	-0.0208	0.1404**	0.0681	-0.1167
	(0.0880)	(0.0853)	(0.0821)	(0.0658)	(0.0760)	(0.0862)
t−1 × Robot	0.1231	0.0605	-0.0496	0.0964	0.0589	-0.1496*
	(0.0960)	(0.0900)	(0.0781)	(0.0601)	(0.0842)	(0.0816)
t × Robot	0.2151**	0.1529	0.1431*	0.1912***	0.2361***	0.0931
	(0.0937)	(0.1039)	(0.0853)	(0.0673)	(0.0912)	(0.0834)
t+1 × Robot	0.1351	0.0775	-0.0229	0.1252**	0.0726	-0.0485
	(0.1033)	(0.1079)	(0.0933)	(0.0633)	(0.0883)	(0.0872)
			PANEL B: Separations by Occupation			
t−2	0.0566***	0.0297*	0.0165	-0.0145	0.0482***	0.0399**
	(0.0175)	(0.0178)	(0.0145)	(0.0106)	(0.0152)	(0.0161)
t−1	0.0250	0.0432**	0.0400***	-0.0014	0.0429***	0.0457***
	(0.0176)	(0.0182)	(0.0155)	(0.0104)	(0.0149)	(0.0165)
t	0.0662***	0.0595***	0.0645***	0.0014	0.0644***	0.0740***
	(0.0182)	(0.0188)	(0.0155)	(0.0108)	(0.0158)	(0.0170)
t+1	0.0985***	0.0678***	0.0786***	0.0149	0.0790***	0.0783***
	(0.0189)	(0.0189)	(0.0159)	(0.0109)	(0.0166)	(0.0174)
t−2 × Robot	-0.0217	-0.0357	0.0092	0.1356**	0.0994	-0.0686
	(0.0930)	(0.0818)	(0.0726)	(0.0569)	(0.0733)	(0.0803)
t−1 × Robot	0.0896	-0.0658	0.0505	0.0711	0.0578	0.0554
	(0.0831)	(0.0755)	(0.0768)	(0.0643)	(0.0780)	(0.0820)
t × Robot	0.1616*	0.0710	-0.0748	0.0306	0.0693	-0.0344
	(0.0945)	(0.0849)	(0.0741)	(0.0607)	(0.0810)	(0.0821)
t+1 × Robot	0.1761*	0.0485	-0.0117	0.1159*	0.1766**	0.0929
	(0.1002)	(0.0854)	(0.0807)	(0.0622)	(0.0852)	(0.0845)

Notes: (i) This table reports the event-study results based on Equation (5.1). The number of observations is 10390 across all columns. (ii) The plant fixed effect is included. (iii) The dependent variables are the number of new hires (Panel A) and the number of separations (Panel B) for each of the six Blossfeld occupation groups. They are rescaled by the inverse hyperbolic sine transformation. (iv) Standard errors in parenthesis are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4.6: Worker Flows by Age

	Hires			Separations		
	(1) young (20−34)	(2) mid-age (35-54)	(3) old (55−65)	(4) young (20−34)	(5) mid-age (35-54)	(6) old (55−65)
t−2	-0.0527***	-0.0507**	-0.0292	0.0090	0.0261	0.0376**
	(0.0190)	(0.0204)	(0.0179)	(0.0182)	(0.0199)	(0.0183)
t−1	-0.0409**	-0.0350*	-0.0176	0.0127	0.0074	0.0515***
	(0.0194)	(0.0207)	(0.0181)	(0.0191)	(0.0204)	(0.0182)
t	0.0161	-0.0060	0.0498***	0.0193	0.0611***	0.0867***
	(0.0200)	(0.0216)	(0.0186)	(0.0196)	(0.0203)	(0.0182)
t+1	-0.0010	0.0088	0.0827***	0.0454**	0.0845***	0.1072***
	(0.0209)	(0.0223)	(0.0187)	(0.0198)	(0.0215)	(0.0193)
t−2 × Robot	0.0425	-0.0447	0.1193	-0.1069	0.0982	0.0915
	(0.0842)	(0.0856)	(0.0944)	(0.0759)	(0.0748)	(0.0786)
t−1 × Robot	0.0683	0.0497	0.0828	-0.1044	0.1608*	0.0690
	(0.0897)	(0.0942)	(0.0997)	(0.0780)	(0.0849)	(0.0815)
t × Robot	0.2408***	0.2788***	0.1366	0.0020	0.1392	0.0883
	(0.0893)	(0.0981)	(0.0965)	(0.0812)	(0.0904)	(0.0837)
t+1 × Robot	0.1486	0.1870*	0.0572	0.0410	0.1969**	0.1551*
	(0.0909)	(0.1019)	(0.0895)	(0.0750)	(0.0842)	(0.0922)

Notes: (i) This table reports the event-study results based on Equation (5.1). The number of observations is 10390 across all columns. (ii) The plant fixed effect is included. (iii) The dependent variables are the number of new hires and the number of separations for each of the three age groups. They are rescaled by the inverse hyperbolic sine transformation. (iv) Standard errors in parenthesis are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4.7: Staggered DiD Estimation based on Sun and Abraham (2021)

	Overall			Age		
	employment	hires	separations	young (20−34)	mid-age (35-54)	old (55−65)
t−2 × Robot	0.0055	-0.0037	0.0218	0.0178	-0.0016	0.0456*
	(0.0125)	(0.0694)	(0.0603)	(0.0194)	(0.0130)	(0.0240)
t−1 × Robot	0.0242	0.0959	0.0326	0.0710***	0.0117	0.0415
	(0.0161)	(0.0769)	(0.064)	(0.0271)	(0.023)	(0.0256)
t × Robot	0.0457**	0.2192***	0.0756	0.1158***	0.0468*	0.0212
	(0.0228)	(0.0737)	(0.0664)	(0.0343)	(0.0278)	(0.0358)
t+1 × Robot	0.0372	0.1639**	0.1308*	0.1296***	0.0427	0.0200
	(0.0272)	(0.0782)	(0.0702)	(0.0395)	(0.0332)	(0.0400)
	Occupation					
	simple manual	qualified manual	technician engineer	manager	service	admin
t−2 × Robot	0.0097	0.0015	0.0240	0.0316	0.0196	0.0158
	(0.0233)	(0.0175)	(0.0193)	(0.0297)	(0.0198)	(0.0215)
t−1 × Robot	0.0215	0.0405	0.0144	0.0243	0.0312	-0.0100
	(0.0289)	(0.0286)	(0.0295)	(0.0355)	(0.0311)	(0.0271)
t × Robot	0.0068	0.0608	0.0752**	0.0832**	0.0645	0.0221
	(0.0477)	(0.0436)	(0.0351)	(0.0407)	(0.0484)	(0.0301)
t+1 × Robot	0.0300	0.0525	0.0752**	0.1007**	0.0738	0.0223
	(0.0561)	(0.0551)	(0.0381)	(0.0475)	(0.0529)	(0.0322)

Notes: (i) This table reports the event-study results using the Sun-Abraham approach. All observations from 2012 to 2019 are included ($N = 17885$). We report the point estimates for $t-2$ to $t+1$ (with $t-3$ as the base year). (ii) The plant and year fixed effects are included. (iii) The dependent variables are plant-level employment, number of new hires, number of separations, employment in each of the six Blossfeld occupation groups and the three age groups. They are based on the BHP data and rescaled by the inverse hyperbolic sine transformation. (iv) Standard errors in parenthesis are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4.1: Robustness: IHS Transformation for Employment and Worker Flows

	(1) Employment	(2) Hires	(3) Separations
	PANEL A: Excluding Plants with <20 Employees ($N = 6950$)		
t−2 × Robot	0.0138	0.0729	-0.0217
	(0.0105)	(0.0712)	(0.0608)
t−1 × Robot	0.0212	0.1106	0.0299
	(0.0157)	(0.0736)	(0.0646)
t × Robot	0.0494**	0.2506***	0.0168
	(0.0241)	(0.0778)	(0.0681)
t+1 × Robot	0.0618**	0.1655**	0.0549
	(0.0275)	(0.0805)	(0.0711)
	PANEL B: Percentile Regressions ($N = 10390$)		
t−2 × Robot	0.2822	1.4431	0.6803
	(0.2020)	(1.4548)	(1.4152)
t−1 × Robot	0.3399	2.3144	2.4795*
	(0.3025)	(1.6429)	(1.3790)
t × Robot	0.6178	3.9789***	1.6825
	(0.4078)	(1.4762)	(1.5084)
t+1 × Robot	0.6725	2.9155*	2.9470**
	(0.5188)	(1.7010)	(1.4993)
	PANEL C: Log Transformed		
t−2 × Robot	0.0143	0.0066	0.0278
	(0.0103)	(0.0662)	(0.0584)
t−1 × Robot	0.0206	0.0676	0.0745
	(0.0153)	(0.0728)	(0.0588)
t × Robot	0.0480**	0.2035***	0.0855
	(0.0234)	(0.0757)	(0.0644)
t+1 × Robot	0.0512*	0.1170	0.1510**
	(0.0282)	(0.0780)	(0.0660)
N	10390	9205	9306
	PANEL D: Level as Share of Base-year Employment ($N = 10390$)		
t−2 × Robot		0.0630	0.0431
		(0.0829)	(0.0647)
t−1 × Robot		0.1041	0.1061*
		(0.0959)	(0.0614)
t × Robot		0.2621***	0.1110
		(0.0975)	(0.0742)
t+1 × Robot		0.1673*	0.2175**
		(0.0929)	(0.0876)

Notes: (i) This table reports the event-study results based on Equation (5.1). (ii) The plant and relative time fixed effects are included. (iii) The dependent variables, based on BHP data, are plant-level employment, number of new hires, and number of separations. (iv) Panel A displays treatment effects for a sample that excludes plants with less than 20 employees. The dependent variables are re-scaled by the inverse hyperbolic sine transformation. (v) Panel B displays treatment effects for percentile regressions, where the dependent variable is measured in percentile $(0 - 100)$ based on the plant-level distribution of the original outcome variable for each time period. (vi) Panel C displays treatment effects for log-transformed dependent variables. (vii) Panel D displays treatment effects for worker flow variables in levels as a share of base-year plant size, where estimates are re-scaled with the base year sample mean to arrive at a percent change interpretation. (viii) Standard errors in parenthesis are clustered at the plant level. (ix) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Chapter 5

Robots and Female Employment in German Manufacturing[1]

5.1 Introduction

With the advancement of automation technologies, robotics in particular, there is growing concern about how they affect employment and wages. Applications of automation to more routine tasks are thought to generally increase displacement risks (Acemoglu and Restrepo, 2018). As robots are heavily used in the generally male-dominated manufacturing sector, the estimated effects are driven mainly by male employment. Less attention has been paid thus far to the potentially differential impact of robots on women and men. Whereas Black and Spitz-Oener (2010) find a lower routine task share for women than for men in Germany, Brussevich et al. (2019) report higher routine task intensity for women in a cross-country setting and for Germany in particular. Furthermore, male workers have a comparative advantage in performing physical manual jobs, which are more susceptible to robotization (Acemoglu et al., 2022). Much less is known about gender bias in the employment-increasing effects of robots, i.e., the productivity and reinstatement channels (Acemoglu and Restrepo, 2018).[2] Therefore, there is no clear-cut prediction a priori as to how robots affect female employment.

The existing empirical evidence, based predominantly on aggregate local labor market studies, is mixed. Robots are found to lower the employment and wages of men

[1] This chapter is joint work with Liuchun Deng, Steffen Müller, and Jens Stegmaier and is published in AEA Papers and Proceedings (vol.113, pp. 224-28, May 2023).

[2] Aksoy et al. (2021) report that the productivity effect benefits skilled men in a subset of European countries not including Germany.

and women in the US, with the effect being more negative for men (Acemoglu and Restrepo, 2020; Anelli et al., 2021; Ge and Zhou, 2020). Acemoglu and Restrepo (2022) report that automation slightly reduces the US gender wage gap in general equilibrium. However, Aksoy et al. (2021) and Blanas et al. (2019) show no impact of robots on gender inequality in Germany and even a slight increase in Europe as a whole.

In the robot-intensive German economy, approximately 57% (64%) of women (men) aged between 15 and 65 were employed in 2019.[3] Women account for 46% of total employment in Germany but for only 25% of total employment in manufacturing. Whereas 52% (88%) of female (male) workers work full-time, these percentages are much higher in manufacturing (70% for female versus 97% for male workers).

We use German plant-level data to study the effect of robots on female employment in the manufacturing sector for the period from 2014 to 2018. We address a major data limitation in the literature: whereas most studies rely on industry-level robot data, this is the first paper to empirically examine the gendered labor market outcome of robots at the production-unit level. We further draw on worker-level social security data to also include the occupational dimension of female employment outcomes.

5.2 Data

We draw plant-level data on robots from the IAB Establishment Panel, an annual high-quality survey of nearly 16,000 German plants. The survey data are nationally representative. In the 2019 wave, we included a dedicated section on robot use. In particular, we asked whether each plant had used robots in the past five years and, if so, how many robots were used in each year from 2014 to 2018. We adopted the ISO definition of robots and performed extensive pretesting and consistency checks to ensure data quality (Plümpe and Stegmaier, 2022). The robot data were then linked with social security records of establishments (IAB Establishment History Panel, BHP)

[3] These and the following numbers are derived from the Employment Statistics of the German Federal Employment Agency and, as our micro data, pertain to employment subject to social security payments. The data thus exclude self-employed workers and civil servants.

and workers (IAB Employment History, BeH), from which we constructed plant-level employment information by gender and occupation.[4]

Our analysis is based on plants in the manufacturing sector with at least 10 employees. A plant is identified as a robot adopter if it had no robots in 2014 but a positive number of robots in subsequent years.[5] By construction, robot adoption could have taken place in one of the four years from 2015 to 2018, and correspondingly, there are four treatment groups. We organize the sample in relative time centered around the year of robot adoption. The control group consists of plants that neither already used robots in 2014 nor adopted them later. The control group is split randomly into four equally sized groups, each of which is assigned to one of the four treatment groups. The relative time for each control group follows the treatment group that it is assigned to.[6] We track each plant from three years before adoption to one year after adoption. The final sample is a five-year balanced panel that consists of 1728 manufacturing plants, among which 114 plants are robot adopters: 24 plants adopted robots in 2015, 27 in 2016, 20 in 2017, and 43 in 2018.

Robot adopters have a lower share of female employees. The average female employment share across robot-adopting plants is 24%, compared with 29% for nonadopters.[7] When we restrict our attention to full-time female employees, plant-level female shares are comparable between robot adopters (17%) and nonadopters (18%). As is now well known in the literature, robot adopters are significantly larger than nonadopters. Despite having a relatively low female employment share, robot adopters on average employ 55 female workers, whereas the mean female employment of nonadopters is 25.

Female employees in robot adopters have, on average, lower qualifications than those in nonadopters. We group occupations into three categories by their level of job

[4] The BeH data we used is customized data extract from BeH version 10_05_01. The DOI to the BHP data is 10.5164/IAB.BHP7519.de.en.v2 and the DOI to the IAB Establishment Panel is 10.5164/IAB.IABBP9319.de.en.v1.

[5] To focus on the effect of first-time adoption, we exclude plants with reported robot use in 2014, the first year for which we have plant-level robot information.

[6] The relative time approach sidesteps the problems with multiple-period difference-in-difference settings thematized, e.g., in Goodman-Bacon (2021).

[7] All descriptive statistics are measured as of three years prior to robot adoption. We do not apply survey weights. Tables in the online appendix include sample means of all dependent variables separately for adopters and non-adopters.

qualification: (i) low-qualified occupations are unskilled manual, service, commercial and administrative occupations; (ii) medium-qualified occupations are skilled manual, service, commercial and administrative occupations; and (iii) high-qualified occupations are managers, engineers, technicians, and other professionals.[8] The plant-level share of the low-qualified out of all female workers is 45% and the medium-qualified (high-qualified) share is 45% (11%). At plants that did not adopt robots, the corresponding figures are 38%, 49%, and 13%.

5.3 Empirical Framework

The estimation equation for our event-study approach is

$$Y_{it} = \alpha_i + \sum_{k=-2}^{1} \beta_k \, T_t^k + \sum_{k=-2}^{1} \gamma_k \; Robot_i \, T_t^k + \epsilon_{it},$$

which relates plant i's outcome variable of interest Y_{it} in relative time t to the event of robot adoption. We control for an individual fixed effect α_i. T_t^k is a relative time dummy that equals one if $t = k$. $Robot_i$ is the time-invariant treatment group indicator for robot adopters, and the main coefficient of interest is γ_k. It measures the development of Y_{it} in the treatment group relative to the outcome in the control group. The $t = -3$ period serves as the reference period so point estimates are thus interpreted relative to three years prior to adoption. Outcome variables Y_{it} always pertain to *female* employment, hiring, and separations, respectively.

5.4 Results

Table 5.1 reports the event-study results for female employment, hires, and separations. The first (last) three columns present the point estimates for all (full-time) female employees. As Column (1) shows, robot adoption does not reduce female employment.

[8] The three main categories are based on the occupation categories created by Blossfeld (1987) and available in the IAB BHP data. The original Blossfeld categories provide precise definitions for which skilled and unskilled occupations are explicitly distinguished. For instance, medium-skilled workers usually have formal vocational training.

Table 5.1: Robot Adoption and Female Employment, Hires, and Separations

	All Female			Full-Time Female		
	(1) Empl.	(2) Hire	(3) Sepr.	(4) Empl.	(5) Hire	(6) Sepr.
γ_{-2}	0.2157	-0.3427	-0.3368	0.2593	0.8278	-0.6389
	(0.9426)	(1.0887)	(0.8218)	(0.8588)	(0.8132)	(0.7436)
γ_{-1}	-0.1403	-0.4191	0.1586	0.3633	1.2435	-0.0973
	(1.2578)	(1.3246)	(0.7825)	(1.0871)	(0.6525)	(0.7258)
γ_0	2.8846	2.8465	0.0433	3.5126	3.4904	0.0964
	(2.4821)	(2.0501)	(0.8954)	(2.4866)	(1.8016)	(0.8857)
γ_1	2.5832	0.0152	0.5381	3.5056	1.2453	0.3589
	(2.5112)	(0.7165)	(1.0122)	(2.7992)	(0.5917)	(0.9590)
R^2	0.0059	0.0091	0.0033	0.0072	0.0124	0.0035

This table reports event-study results based on the model described in the text (number of observations = 8640). (i) The dependent variables are obtained directly from the plant-level BHP data. They are female employment in Columns (1) and (4), female hires in Columns (2) and (5), and female separations in Columns (3) and (6). (ii) Columns (1)–(3) refer to all female employees, whereas Columns (4)–(6) refer to full-time female employees only. (iii) Plant and (relative) time fixed effects are included. (iv) Standard errors in parentheses are clustered at the plant level. (v) Within R^2 is reported in the last row.

In fact, the estimates for γ_0 and γ_1, albeit noisily estimated, suggest that following robot adoption, female employment at robot-adopting plants increases relative to that of nonadopters. In the year of adoption, there is a relative increase of 2.88 female workers. Compared with the reference-year adopters sample mean of 55, the point estimate for γ_0 suggests that robot adoption raises female employment on average by approximately 5%.

The increase in employment is not driven by a pretrend, and the estimated relative time fixed effects show a slight increase in female employment for the control group.[9] This finding contrasts with the negative association between robots and female manufacturing employment documented for US local labor markets (Acemoglu and Restrepo, 2020).

The increase in female employment is accompanied by a substantial increase of 2.85 persons (40% increase against adopters sample mean) in female hires in the year of

[9] Due to space limitations, we omit the estimates of β_k here and report them in the online appendix tables.

Table 5.2: Robot Adoption and Female Employment by Occupation Group

	(1) Low-qualified	(2) Medium-qualified	(3) High-qualified
γ_{-2}	-0.3711	0.8289	-0.2002
	(0.4563)	(0.7038)	(0.1407)
γ_{-1}	-0.6300	0.8736	-0.2195
	(0.7622)	(0.7661)	(0.2003)
γ_0	0.1995	2.6282	-0.0198
	(1.1635)	(1.8695)	(0.2855)
γ_1	0.1430	2.4217	-0.0896
	(1.3139)	(1.7995)	(0.3421)
R^2	0.0006	0.0079	0.0064

This table reports event-study results based on the model described in the text (number of observations = 8640). (i) The dependent variables, plant-level female employment by occupation group, are computed from the worker-level BeH data. (ii) Low-qualified occupations are unskilled manual, service, commercial and administrative occupations. Medium-qualified occupations are skilled manual, service, commercial and administrative occupations. High-qualified occupations are managers, engineers, technicians, and other professionals. (iii) Plant and (relative) time fixed effects are included. (iv) Standard errors in parentheses are clustered at the plant level. (v) Within R^2 is reported in the last row.

robot adoption (Column 2). Job separations increase with a smaller magnitude one year later (Column 3). To see whether the increase in female employment is driven by additional part-time jobs, we report in the next three columns the regression results for female full-time workers. Results are more pronounced: an increase in full-time employment by 10% accompanied by a substantial increase in hiring by 107%.

Next, we turn to the effect of robots on female employment by occupation group. The results in Table A5.2 demonstrate that the positive association between robot adoption and female employment is driven largely by medium-qualified occupations. In particular, Column (2) suggests that robot adoption raises female employment by 2.63 workers (15% increase against adopters sample mean) for medium-qualified occupations, and this positive employment effect persists after robot adoption. In contrast, Columns (1) and (3) show no strong association between robot adoption and female employment in either low- or high-qualified occupations. Interestingly, female employment in high-qualified occupations experiences a steady increase for the control group over the sample period. Hence, robot adopters keep up with this trend and additionally upgrade their female workforce with well-trained medium-qualified workers.

5.5 Conclusion

Robots are heavily used in male-dominated manufacturing, and any overall employment effects are thus driven mainly by male workers. Little is known about the effects of robots on female employment, and no studies have used data on robot use at the production-unit level. Using German plant-level data, we document that robot adoption yields a modest gain in female employment driven by increased hiring and accompanied by a substantial increase in job churning. The positive effect on female employment is concentrated on medium-qualified occupations and full-time workers. Therefore, female workers seem to participate in the positive firm-level employment effect of robots in Europe documented in Koch et al. (2021) for Spain, in Acemoglu et al. (2020) for France, and in studies presented at the 2023 ASSA meetings (Aghion et al., 2023; Deng et al., 2023) using data for France and Germany, respectively.

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Appendix

Table A5.1: Robot Adoption and Female Employment, Hires, and Separations

	All Female			Full-time Female		
	(1) Empl.	(2) Hire	(3) Sepr.	(4) Empl.	(5) Hire	(6) Sepr.
β_{-2}	0.2404	-0.1047	-0.0843	0.1004	-0.0998	-0.0979
	(0.1145)	(0.0979)	(0.1061)	(0.0893)	(0.0702)	(0.0794)
β_{-1}	0.4473	-0.0458	0.0081	0.1543	-0.1295	-0.0694
	(0.2070)	(0.1118)	(0.1323)	(0.1517)	(0.0873)	(0.1106)
β_0	0.5979	0.0043	0.1146	0.2243	-0.0167	-0.0087
	(0.2432)	(0.1139)	(0.1100)	(0.1838)	(0.0787)	(0.0814)
β_1	0.7677	0.3445	0.4356	0.2751	0.1933	0.2639
	(0.3266)	(0.1226)	(0.1553)	(0.2424)	(0.0890)	(0.1125)
γ_{-2}	0.2157	-0.3427	-0.3368	0.2593	0.8278	-0.6389
	(0.9426)	(1.0887)	(0.8218)	(0.8588)	(0.8132)	(0.7436)
γ_{-1}	-0.1403	-0.4191	0.1586	0.3633	1.2435	-0.0973
	(1.2578)	(1.3246)	(0.7825)	(1.0871)	(0.6525)	(0.7258)
γ_0	2.8846	2.8465	0.0433	3.5126	3.4904	0.0964
	(2.4821)	(2.0501)	(0.8954)	(2.4866)	(1.8016)	(0.8857)
γ_1	2.5832	0.0152	0.5381	3.5056	1.2453	0.3589
	(2.5112)	(0.7165)	(1.0122)	(2.7992)	(0.5917)	(0.9590)
Within R^2	0.0059	0.0091	0.0033	0.0072	0.0124	0.0035
Adopters Mean	54.69	7.04	6.55	36.09	3.25	4.45
Nonadopters Mean	25.31	3.63	3.37	16.51	2.00	1.99

Notes: This table reports event-study results based on the model described in the paper (number of observations = 8640). (i) The dependent variables are obtained directly from the plant-level BHP data. They are female employment in Columns (1) and (4), female hires in Columns (2) and (5), and female separations in Columns (3) and (6). (ii) Columns (1)–(3) refer to all female employees whereas Columns (4)–(6) refer to full-time female employees, only. (iii) Plant and (relative) time fixed effects are included. (iv) Standard errors in parenthesis are clustered at the plant level. (v) The mean of dependent variables is calculated for the treatment and control group separately in the reference year as of three years prior to adoption.

Table A5.2: Robot Adoption and Female Employment by Occupation Group

	(1) Low-qualified	(2) Medium-qualified	(3) High-qualified
β_{-2}	-0.0149	0.0483	0.1914
	(0.0770)	(0.0501)	(0.0511)
β_{-1}	0.0248	0.1791	0.2633
	(0.1250)	(0.0906)	(0.0840)
β_{0}	0.0198	0.2577	0.3532
	(0.1459)	(0.0998)	(0.1084)
β_{1}	0.0149	0.2800	0.5019
	(0.1947)	(0.1445)	(0.1397)
γ_{-2}	-0.3711	0.8289	-0.2002
	(0.4563)	(0.7038)	(0.1407)
γ_{-1}	-0.6300	0.8736	-0.2195
	(0.7622)	(0.7661)	(0.2003)
γ_{0}	0.1995	2.6282	-0.0198
	(1.1635)	(1.8695)	(0.2855)
γ_{1}	0.1430	2.4217	-0.0896
	(1.3139)	(1.7995)	(0.3421)
Within R^2	0.0006	0.0079	0.0064
Adopters Mean	33.29	17.18	5.44
Nonadopters Mean	11.94	9.99	3.68
Adopter Empl. Share	0.4473	0.4474	0.1053
Nonadopter Empl. Share	0.3792	0.4876	0.1332

This table reports event-study results based on the model described in the paper (number of observations = 8640). (i) The dependent variables, plant-level female employment by occupation group, are computed from the worker-level BeH data. (ii) Low-qualified occupations are unskilled manual, service, commercial and administrative occupations. Medium-qualified occupations are skilled manual, service, commercial and administrative occupations. High-qualified occupations are managers, engineers, technicians, and other professionals. (iii) Plant and (relative) time-fixed effects are included. (iv) Standard errors in parenthesis are clustered at the plant level. (v) The mean of dependent variables and occupation-level employment share are calculated for the treatment and control group separately in the reference year as of three years prior to adoption. We compute the employment share by taking the ratio of female employment in a given occupation group to total female employment at the plant level and then averaging it across plants.