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Abstract

Using a newly collected dataset of robot use at the plant level from 2014 to 2018, we provide the first microscopic portrait of robotisation in Germany and study the potential determinants of robot adoption. Our descriptive analysis uncovers five stylised facts concerning both extensive and, perhaps more importantly, intensive margin of plant-level robot use: (1) Robot use is relatively rare with only 1.55% German plants using robots in 2018. (2) The distribution of robots is highly skewed. (3) New robot adopters contribute substantially to the recent robotisation. (4) Robot users are exceptional along several dimensions of plant-level characteristics. (5) Heterogeneity in robot types matters. Our regression results further suggest plant size, low-skilled labour share, and exporter status to have strong and positive effect on future probability of robot adoption. Manufacturing plants impacted by the introduction of minimum wage in 2015 are also more likely to adopt robots. However, controlling for plant size, we find that plant-level productivity has no, if not negative, impact on robot adoption.

Keywords: robots, robot adoption, automation, labour, productivity, plant-level

JEL classification: J24, O14, O33

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1 Introduction

The robots are coming. The recent advances of automation technology, robotics and artificial intelligence in particular, have sparked a heated debate over the future of labor and human society at large. To better understand the recent wave of automation, a nascent literature examines the drivers and consequences of (industrial) robots using firm- or plant-level data from mainly a few European countries.[1] Perhaps surprisingly, there is little systematic microeconomic data on the use of robots in Germany, a country especially known for robot production and adoption, and thus, the existing work on the rise of robots in Germany, Dauth et al. (2019) most notably, relies solely on the industry-level dataset from the International Federation of Robotics (IFR).[2] Using a newly collected plant-level data in Germany, this paper attempts to fill this void.

In this paper, we leverage the plant-level information on the use and adoption of robots in the 2019 IAB Establishment Survey to portray the state, the recent development, correlates, and potential determinants of robot use and adoption in Germany. 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 owned more than half of the total robot stock in 2018. Third, the new robot adopters (the extensive margin) contributed substantially to growth in the share of robot users and the aggregate stock of robots from 2014 to 2018. Fourth, robot users are exceptional. Robot users in 2018 are found to be larger, have higher labor productivity, invest more, are more likely to export, and adopt up-to-date technology than non-robot-using plants. We term those conditional gains from robot installation as *robotization premia*. Last, plants use different types of robots and heterogeneity in robot types matters for an array of plant-level characteristics.

We further examine the potential determinants of robot adoption at the plant level. Our regression results demonstrate plant size to be the most robust predictor of future robot adoption. According to our preferred estimate, a one-standard-deviation increase in the total employment in 2014 leads to a 1.6-percentage-point increase in the probability of robot adoption from 2015 to 2018, compared with the unconditional probability of robot adoption which is 2.48% over the same period. Conditional on plant size, both low-skilled labor intensity and export status have strong and positive effects on robot adoption, while sub-sample regressions suggest that the effect of low-skilled labor intensity is only found significant within the manufacturing sample. Manufacturing plants that raised wages due to the introduction of minimum wage in 2015 are also found to be more likely to adopt robots. Interestingly, we document that, when controlling for plant size, productivity has little, if not negative, effect on robot adoption. This result questions the overwhelmingly positive effect of productivity on robotization predicted by the existing theoretical work (Koch et al., 2019; Humlum, 2019).

To our knowledge, this paper is the first to collect and use the plant-level robot data to investigate robotization in Germany. Following the seminal paper by Graetz and Michaels (2018), the cross-

[1] See Acemoglu et al. (2020) and Bonfiglioli et al. (2019) for France, Humlum (2019) for Denmark, Koch et al. (2019) for Spain, and Barth et al. (2020) for Norway. See also Cheng et al. (2019) for robotization in China.

[2] The only exception is Zator (2019) which exploits the broader measures of automation (including robots and CNC machines) and digitalization in the 2016 and 2017 waves of the IAB Establishment Panel.

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

country industry-level IFR dataset has been widely used in empirical studies (Acemoglu and Restrepo, 2019; Dauth et al., 2019; de Vries et al., 2020; Faber, 2020; among many others). Given the significant heterogeneity of robot use in both extensive and intensive margins across plants, industry-level robot information becomes increasingly insufficient for a deeper understanding of the roots and outcomes of robotization. Based on the newly-collected dataset, the stylized facts documented in this paper add to the growing body of microeconomic evidence of robotization.[4]

This paper contributes to the literature on the determinants of robot adoption. The positive effects of plant size, low-skilled labor intensity, and exporter status echo empirical findings using the Spanish firm-level data in Koch et al. (2019). The impact of minimum wage on robot adoption is consistent with the earlier firm-level evidence from China (Fan et al., 2020). The fact that, conditional on firm size being controlled, robot adopters are ex ante not more productive while ex post robot using plants enjoy higher productivity suggests that laggard plants may attempt to achieve productivity catchup by replacing their workers with robots, a channel largely overlooked in the existing theoretical framework. By focusing on the effects of plant characteristics, our results complement Acemoglu and Restrepo (2018a) and Zator (2019) which examine the labor market factors, population aging and labor scarcity in particular, of automation.

Last but not least, the rich robot information in our dataset enables us to explore two aspects that are largely neglected in the literature, namely, robotization in the manufacturing versus non-manufacturing sector and heterogeneity in robot types. Similar to the industry-level pattern in the IFR data, we find the non-manufacturing sector is at a much earlier stage of robotization. More importantly, we note that skill composition and the introduction of minimum wage do not play a significant role in robot adoption decision for non-manufacturing plants. Regression results further reveal that robotization premia vary significantly across plants using different types of robots.

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

2 The Data and Stylized Facts

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[5]. 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 most recent 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 axis 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,

[4] Another strand of the literature exploits alternative measures of the broader phenomenon of automation at the microeconomic level (Bessen et al., 2019; Aghion et al., 2020; Domini et al., 2020).

[5] We use the IAB Establishment Panel, Waves 2013 -2019. DOI: 10.5164/IAB.IABBP9318.de.en.v1. For more information on the IAB Establishment Panel, see Bechmann et al. (2019).

(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.[6] An additional survey round was conducted for a subset of plants which we suspect may have given inaccurate answers to robot questions to ensure the quality and consistency of the dataset.

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; Bonfiglioli et al., 2019; Humlum, 2019; Barth et al., 2020).[7] 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. (2019), while we also obtain direct robot information in the intensive margin.

The plant-level data, aggregated to the industry-level, is broadly consistent and highly correlated with the industry-level IFR data for Germany.[8] Given the panel structure, we incorporate a wide array of plant-level variables from the earlier waves of the IAB Establishment Panel. The resulting dataset is an unbalanced panel of 15,307 plants spanning from 2014 to 2018. Table 1 reports the summary statistics for the main non-robot variables with the definition of each variable explained in the notes. We now turn to the set of stylized facts on robot use and adoption.

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 stratified sample design, survey weights are applied in order to obtain representative results for Germany. We mainly focus on the results with survey weights in the main text and relegate some of the unweighted results to the Appendix.

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 are robot users in Germany. Table 2 reports the share of robot users in 2018 by industry. Column "Weighted" reports the share of robot users with survey weights and thus provides a representative picture of plant-level robotization for the whole country. The manufacturing sector, which has undergone a continued process of robotization for more than five decades,[9] has 8.22% of the plants being robot users in 2018. Even for the most robot-intensive

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

[7] Acemoglu et al. (2020) supplements 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.

[8] For details on cross validation, consistency checks, and imputation, see Plümpe and Stegmaier (Mimeo). Figure A1 in the Appendix provides a general industry-level comparison between the two datasets.

[9] For a brief history of industrial robots, see the IFR 2012 report, *History of Industrial Robots: From the First Installation until Today.*

manufacturing industries such as plastics and motor vehicles, around three quarters of the plants did not install a single robot. 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. 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 unweighted share, but the main pattern persists: robot use is relatively rare. It should be nevertheless noted that these robot using plants employed 3.2 million workers in 2018, which accounted for about 8% of the total labor force in Germany.

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 owned by top 5% of robot using plants in Germany, while within the survey sample 85% of the total robot stock is owned by top 5% of robot using plants.

According to the first panel of Figure 1, manufacturing plants in the top decile ranked by the robot count on average had 40 robots in 2018, 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 had on average 141 robots.[10] Based on the same sorting of plants, the second panel of Figure 1 further demonstrates that high concentration of robots is not merely 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, which implies that the distribution of robots is much more skewed than the employment distribution across plants.

It is worth noting that high concentration of robots in the manufacturing sector is not entirely due to the large automobile plants. Indeed, the plants with highest number of robots are mainly in the motor vehicle industry but the robot distribution with the automobile plants excluded remains very skewed. In fact, an inspection of the robot distribution by industry suggests that robots are highly concentrated in almost all manufacturing industries.

In contrast, the distribution of robots is significantly less skewed 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 may reflect the different nature of robotic technology (for example, service robots) and the early stage of robotization in the non-manufacturing sector.

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 growth in both the share of robot users and the total robot stock. Figure 2 compares the share of robot users in aggregated industries in 2014 with that in 2018.[11] The share of robot users in the manufacturing sector increased by more than 50% from 5.16% to 8.22%. The user share in the non-manufacturing sector almost doubled from 0.51% to 0.94%. In the motor vehicle industry, one of the most robot-intensive industries, the user share increased from 16.90% to 24.26%.

[10] For the robot distribution without being adjusted for survey weights, which turns out to be more skewed, see Figure A2 in the Appendix.

[11] The user shares in Figure 2 are calculated using survey weights in 2018. Ideally, we should use the 2014 survey sample and the respective weights to calculate the user share in 2014. As the robot data was only collected in 2019 through retrospective questions, we do not have fully representative data for earlier years. We report the same comparison without survey weights in Figure A3 and the pattern remains the same.

It should be noted that out of the 616 plants that used robots from 2014 to 2018 in our survey sample, 104 ($\approx 17\%$) plants reported missing values for 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 using the rate of robot adoption over 2014–2018 based on the plants that reported their robot stocks throughout the sample period. Figure A4 in the Appendix, a companion to Figure 2, 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. However, 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.

Figure 3 plots the growth of robot stock by industry from 2014 to 2018.[12] The industry-level growth is decomposed into the extensive and intensive margins. The extensive margin, illustrated by the light blue bars, is the contribution of robot adopters from 2014 to 2018 to the overall growth of robots, while the intensive margin, illustrated by the dark blue bars, is the contribution of the plants that already used robots in 2014. Two notable features arise. First, the aggregate numbers for the manufacturing sector mask substantial heterogeneity across industries. For example, in the electrical equipment industry, the adopters play a dominant role in robot growth by raising the industry-level robot stock by 260% from 2014 to 2018, which stands in sharp contrast to the motor vehicle industry where robots have been traditionally heavily used. Since the motor vehicle industry has reached a mature phase of robotization with an exceptionally high stock, it significantly downsizes the overall growth in robot stock and the contribution of the extensive margin in the manufacturing sector. Second, the contribution of the extensive margin to growth is much greater in the non-manufacturing sector. The majority of the new robot purchases were made by robot adopters in that sector, consistent with the pattern suggested by the previous figure.[13]

Fact IV: Robot users are exceptional.

Robot users are not only rare but also different from non-users in a number of plant-level characteristics. To capture robotization premia, which draw a direct parallelism with the exporter premia as in Bernard et al. (2007, 2018), we use the 2018 cross-sectional sample to perform a battery of bivariate regressions of the following form

$$X_{ijk} = \alpha + \beta \text{RobotUse}_{ijk} + \phi_j + \psi_k + \gamma \log(\text{Emp}_{ijk}) + \varepsilon_{ijk}, \tag{1}$$

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; Employment_{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, region, and industry), so we do not weight our regressions and present regression results without survey weights throughout this paper for conciseness.[14] We have

[12]Again, survey weights in 2018 are applied to the calculation. For the decomposition without survey weights, see Figure A5 in the Appendix.

[13]Hidden in Figure 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 considered in the extension of the baseline model in Humlum (2019).

[14]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).

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.

According to the estimates of β in Table 3, robot users are larger, have higher labor productivity, make more investments, and are more likely to export and adopt the most updated technology. As Column (2) suggests, the average plant size of the robot users, measured by the employment count, is more than 4 times ($e^{1.422} \approx 4.145$) as large as that of the non-users. Controlling for plant size, Column (3) suggests that the share of low-skilled labor in total employment is 2.7 percentage points higher in robot-using plants. Interestingly, the last two rows of estimates imply that robot users are consistently associated with a *lower* level of product and process improvement and refinement. Columns (4) and (5) report coefficient estimates of the robot use dummy for the manufacturing and non-manufacturing samples separately. The robotization premia are remarkably similar for most of the plant-level characteristics. The only notable difference lies in the share of low-skilled labor: robot users in the manufacturing sector hire disproportionately more low-skilled labor while robot users in the non-manufacturing sector have a smaller share of low-skilled labor than non-users do.

Within the sample of robot users, we examine robotization premia on the intensive margin:

$$X_{ijk} = \alpha + \beta \log(\text{Robot}_{ijk}) + \phi_j + \psi_k + \gamma \log(\text{Emp}_{ijk}) + \varepsilon_{ijk}, \tag{2}$$

where log(Robot) is the log number of robots in a given plant in 2018. According to Table 4, plants that use more robots are larger. A 10% increase in robot stock is associated with 3.93% increase in plant size measured by employment. Due to the small sample size, the point estimates are much less precise for other variables, but the signs of those estimates are largely consistent with our findings on the extensive margin. Plants with more robots have higher labor productivity and employ a larger share of low-skilled labor. The only exception is exporter status. Heavy robot users are not necessarily more likely to export.

Fact V: Heterogeneity of robots matters.

The composition of robots changes over time. Technological progress in the last decade has been shaking the stereotype of (industrial) robots; robots which can be used in collaboration with human workers, usually smaller in size and cheaper in price, are on the rise.[15] To estimate the overall effect of robotization and its evolution, it is important to understand whether collaborative and less expensive robots differ from the prevalent and more expensive non-collaborative robots in their impact on plant-level outcomes.

According to our survey, 49% of the German robot using plants reported using robots that are separated from employees during the 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 reported using robots that cost more than 50,000 Euros (labeled as “expensive robots” henceforth) in 2018. Among those cage robot users, more than 85% of them had 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 had all of their robots purchased at a price above 50,000 Euros, accounting for 45% of the total robot stock.[16]

[15] For a more detailed discussion on “cobots”, collaborative robots, see *World Robotics: Industrial Robots 2018*.

[16] These shares are calculated with survey weights. Within the survey sample, close to 70% of the robot users used

Leveraging the information on robot types, we reexamine robotization premia on both the extensive and intensive margin. In Equation (1), we replace the dummy RobotUse with three dummies corresponding to three types of robot users: plants with all robots being cage robots, plants with all robots being purchased at a price of above 50,000 Euros, and robot users that do not belong to the first two categories. Note that the first two categories are not mutually exclusive. The control group for these extensive margin regressions are the non robot using plants. In Equation (2), we further include the share of cage robots and that of expensive robots to explore the intensive margin among robot users.

According to the first panel in Table 5, robot users are all significantly larger than non-users, but this size premium is largest for plants that solely used cage robots. Conditional on plant size being controlled, cage robot users tend to have higher labor productivity and are much more likely to export. The purchase price of robots does not yield any significant difference in plant characteristics in the extensive-margin regression. In the second panel, we study the role of the composition of robots. Both the share of cage robots and that of expensive robots are significantly positively correlated with plant size. Controlling for the number of robots, a plant that solely uses cage robots is 55% larger than a plant that does not use cage robots; the size premium for the expensive robots is 44%. Consistent with the extensive margin result, a larger share of cage robots is associated with higher probability of export. Those results taken together point to the importance of accounting for heterogeneity of robots.

3 Plant-level Correlates of Robot Adoption

In this section, we explore the potential determinants of robot adoption. In Germany, robot users differed from non-users in several plant characteristics in 2018, as shown in the previous section in Stylized Fact IV. To examine whether these differences existed prior to adoption of robots, we focus on the sample of robot adopters. Using the sample of plants that reported no robot use in 2014, we investigate which plant-level characteristics in the base year correlate with robot adoption in subsequent years. Our baseline cross-sectional regression setting is given by

$$\text{RobotAdp}_{ijk}^{2015-2018} = \alpha + X_{ijk}^{2014}\beta + \phi_j + \psi_k + \varepsilon_{ijk}, \tag{3}$$

where X_{ijk} is a set of plant-level characteristics in 2014 for plant i in industry j and state k; RobotAdp_{ijk} is a dummy variable which equals one if a plant that did not use robots in 2014 newly adopted robots from 2015 to 2018; 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.

In light of a task-based framework of robot adoption with firm heterogeneity as in Koch et al. (2019), we focus on five categories of plant-level characteristics as potential determinants of robot adoption: (1) plant size measured by total employment or business volume; (2) productivity measures such as labor productivity or TFP; (3) skill composition proxied by the share of low-skilled labor or the average wage; (4) change in labor cost due to the introduction of minimum wage in 2015;[17] (5)

cage robots and 65% of them used expensive robots.

[17] The uniform minimum wage was introduced country-wide on January 1, 2015 and the hourly minimum wage was initially set at 8.50 Euros.

exporter status.

Table 6 presents the baseline regression results. Columns (1) – (9) report the results for the full sample. The total employment has a consistently positive effect on future robot adoption. The effect is statistically significant across all specifications. The robust finding of plant size premium in adoption is consistent with the framework as in Humlum (2019) which postulates that robotic technology enter multiplicatively the production function and adoption of robots involves a one-time fixed cost. Columns (2) – (7) present regression results for each of the productivity, skill, labor cost, and trade measures with the total employment being controlled. Interestingly, once plant size is controlled for, productivity does not seem to have any additional effect on robot adoption. The share of low-skilled labor positively impacts robotization. It is consistent with the prediction of the task-based theoretical framework (Acemoglu and Restrepo, 2018b): other things equal, low-skilled labor which has comparative advantage in performing simple and easily automatable tasks is more likely to be replaced by robots. The average wage, arguably a cruder measure of plant-level skill composition, however shows no significant effect on robot adoption. In Column (6), the minimum-wage dummy is defined as whether a plant raised its wages due to the introduction of minimum wage in 2015. For the full sample, the estimate is positive but not significant. Similar to Koch et al. (2019), the exporter status in Column (7) is found to have a positive effect on robot adoption. In Column (8), we include measures of all the five categories of plant-level characteristics simultaneously, the effects of the share of low-skilled labor and exporter status remain positive and statistically significant with increased magnitude. In Column (9), we further control for a wide array of plant-level characteristics which may potentially impact robot adoption. In particular, as documented by Zator (2019) that labor scarcity has a strong effect on adoption of automation technology, we control for plant-level labor scarcity by including a dummy variable that equals one if a plant experiences any of the following staffing problems: skilled workers hard to find; staff shortage; innovation prevented due to lack of qualified staff. Our main results are found to be robust to additional controls.

Our point estimates are not only statistically significant but also economically sizable. According to our preferred estimate in Column (9), a one-standard-deviation increase in log(Employment) in 2014, which is 1.6, leads to a 1.6 percentage point increase in the probability of robot adoption. A one-standard-deviation increase in the share of low-skilled labor in 2014, which is 0.27, yields a 0.57 percentage point increase in adoption probability, while being an exporter increases adoption probability by 3.0 percentage points. Compared with the unconditional probability of robot adoption being 2.48%, the effects of plant size, skill composition, and exporter status on robot adoption are quite substantial in their magnitude.

Columns (10) and (11) in Table 6 further report the regression results for the manufacturing and non-manufacturing samples. The coefficient of employment remains statistically significant and positive in both samples while the magnitude of the estimated effect is much larger in the manufacturing sector. It is worth highlighting that our point estimate of employment for the manufacturing sample is remarkably similar to the results in the panel specification of Koch et al. (2019) using the Spanish manufacturing firm-level data. The estimated coefficient of the share of low-skilled labor doubles in the manufacturing sector while its positive effect largely disappears in the non-manufacturing sector. More interestingly, plants impacted by the minimum wage legislation in 2015 see a significant increase in adoption probability in the manufacturing sector, consistent with the findings in Fan et al. (2020) using the Chinese firm-level data, whereas in the non-manufacturing sector, change in labor cost due to minimum wage seems to have no effect. These comparisons taken together suggest that the determinants of robot adoption may be quite different between the manufacturing and non-manufacturing plants. 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 there. The effect of exporter status on robotization is also stronger in the manufacturing sector, though the effect remains highly significant and economically meaningful in the non-manufacturing sector. 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.

To make it more comparable with the findings in Koch et al. (2019), Table 7 presents the cross-sectional regression results with an output-based measure of plant size, the total business volume. The main difference from Table 6 is that higher labor productivity now implies lower adoption probability and this negative effect is statistically significant for both full and non-manufacturing sample. Competing arguments can be made for how productivity impacts robot adoption decision. On the one hand, more productive firms have higher incentives to adopt robots due to the standard productivity selection channel as in Koch et al. (2019). On the other hand, it is conceivable that laggard plants may attempt to catch up by replacing employees with lower labor productivity with robots. Since the total business volume, as an output measure, is less reliable than the total employment, an input-based measure, in Establishment Panel, we view the negative coefficient of productivity in Table 7 as tentative evidence of calling for an incorporation of the catch-up motive into the model of robot adoption.

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 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

$$\text{RobotAdp}_{ijk}^{t+1,t+2} = \alpha + X_{ijkt}\beta + \phi_{jt} + \psi_{kt} + \varepsilon_{ijkt}, \tag{4}$$

where the base year t is 2014 for the first period and 2016 for the second period and $\text{RobotAdp}_{ijk}^{t+1,t+2}$ is a dummy variable which equals one if a plant that did not use robots in base year t newly adopted robots in the two subsequent years; ϕ_{jt} and ψ_{kt} are the industry-period and state-period fixed effects. We drop all the plant-period pairs if a plant used robots in or prior to the base year of a given period. Therefore, if a plant adopted robots in the first period, its second-period observation is excluded from our sample.

Table 8 reports the regression results using the panel data. The results confirm the findings in the cross-sectional regressions with the only exception that the positive effect of exporter status on robot adoption is no longer significant for the non-manufacturing plants in Column (4). Compared with Table 6, the point estimates for the total employment, the share of low-skilled labor, and exporter status are about half of the cross-sectional estimates with the statistical significance preserved. This is reassuring because we study the effect of plant-level characteristics on robot adoption decision in the subsequent two years in the panel specification as opposed to four years in the cross-sectional setting.

To summarize, we document the effects or lack thereof of five plant-level characteristics on robot adoption decision which have all been theoretically formulated in the existing literature. First, larger plants are more likely to adopt robots and the positive effect of plant size is substantially stronger in the manufacturing sector. Second, conditional on plant size being controlled, robot adopters are ex ante *not* more productive than non adopters. Moreover, plants with a higher share of low-skilled labor and plants impacted by the minimum wage introduction are more likely to adopt robots and the effects are entirely driven by the manufacturing plants. Last, participation in export seems to introduce additional incentives for adoption and the exporter effect is also stronger for the manufacturing plants.

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: (1) Robot use is relatively rare; (2) The distribution of robots is highly skewed; (3) The extensive margin contributes substantially to the recent robotization; (4) Robot users are larger, more productive, and more likely to export and use low-skilled labor more intensively; (5) Heterogeneity of robots matters. Examining the potential determinants of robot adoption, we find plant size, the share of low-skilled labor, and exporter status to have a strong positive impact on future robot adoption, while once plant size is controlled, productivity has no, if not negative, impact on robotization. Introduction of minimum wage also incentivizes plants in the manufacturing sector to adopt robots.

Our empirical results point to several interesting open questions. First, the fact that robot users have higher labor productivity but are ex ante not more productive than non-adopters suggests that robot adoption may have a positive effect on labor productivity as documented by Koch et al. (2019), Bonfiglioli et al. (2019) and Acemoglu et al. (2020) using Spanish and French data and also earlier cross-country regressions as in Graetz and Michaels (2018). Second, it remains unclear if robotization premia in plant size, low-skilled labor intensity, and exporter status are reminiscent of the ex-ante differences due to self-selection of plants into robotization. Third, since our plant-level robot dataset can be readily merged with the worker-level employment biographies in Germany, it is exciting to investigate the wage and employment dynamics for workers in robot-adopting plants. We plan to take up all those questions in our future work.

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Figures

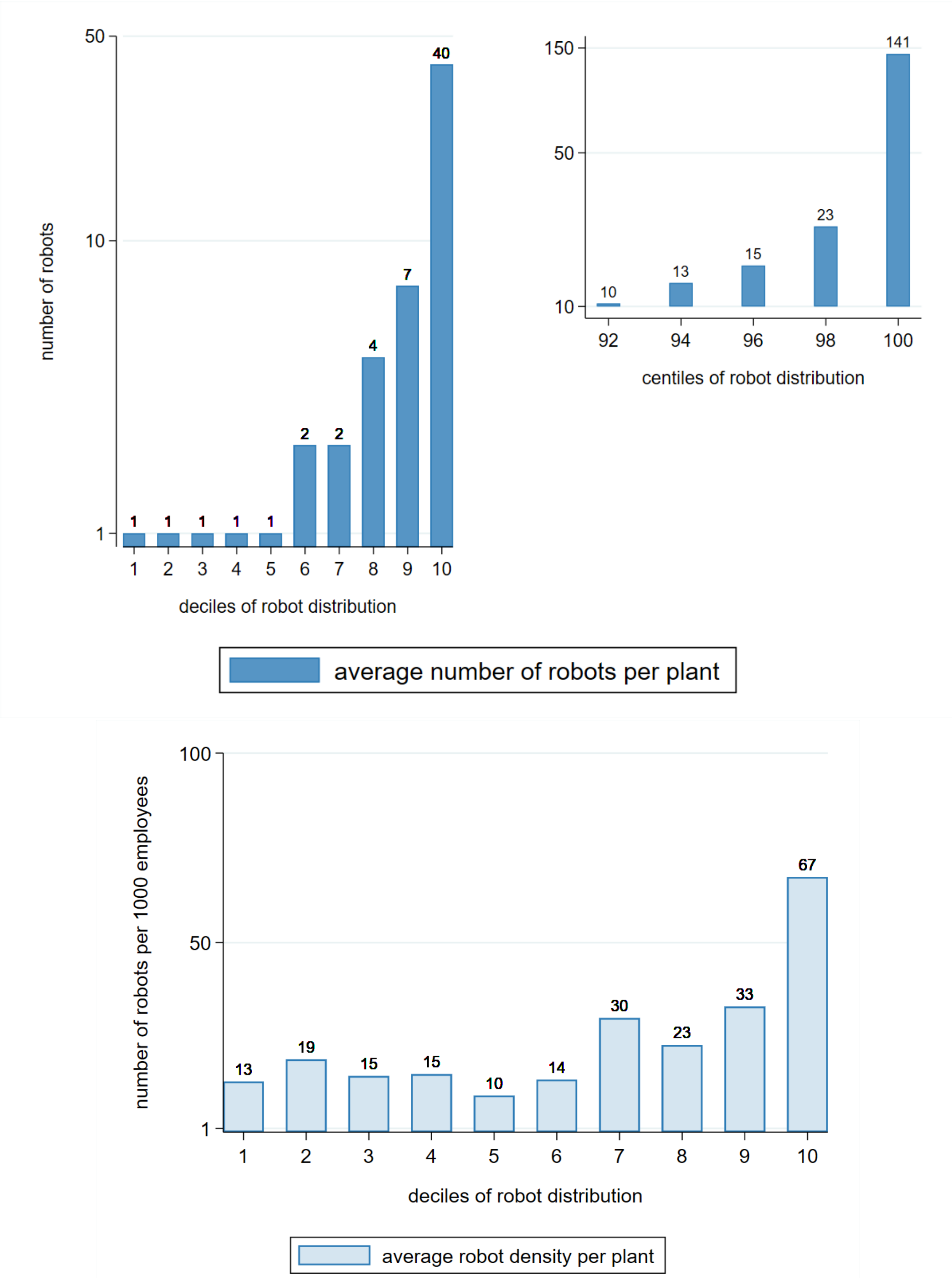

Figure 1: The Intensive Margin: Robot Distribution in the Manufacturing Sector in 2018

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.

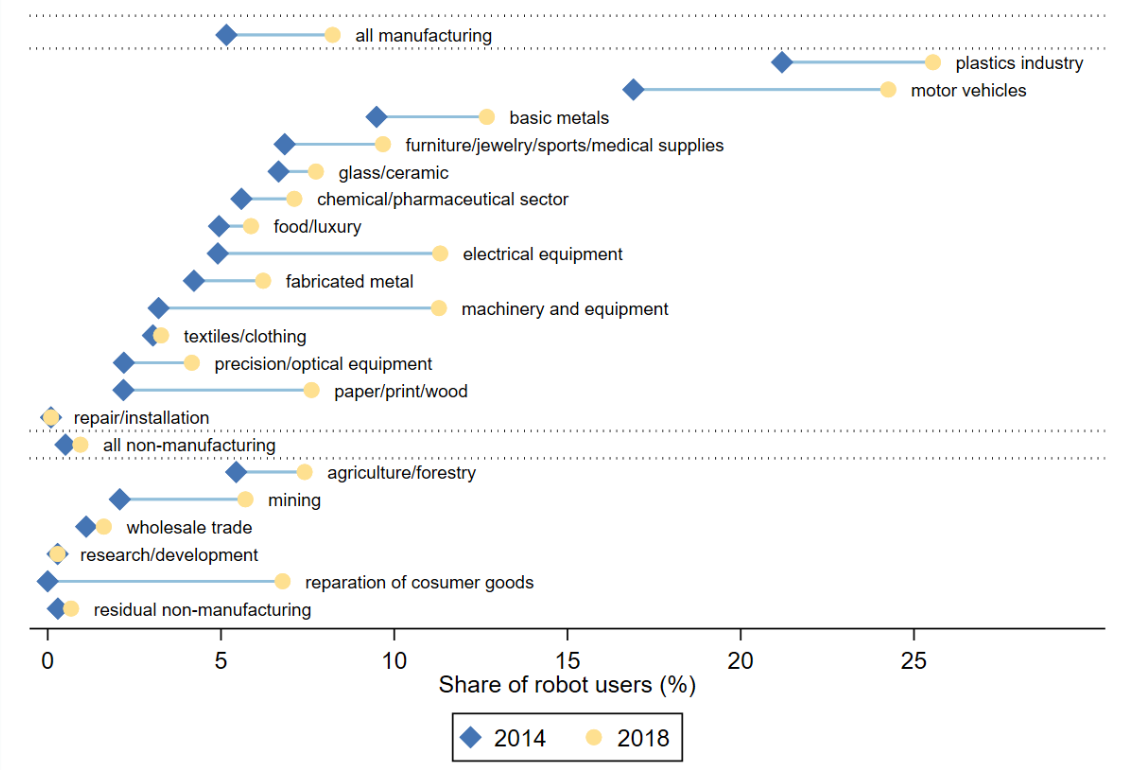

Figure 2: Growth in the Extensive Margin from 2014 to 2018

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 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.

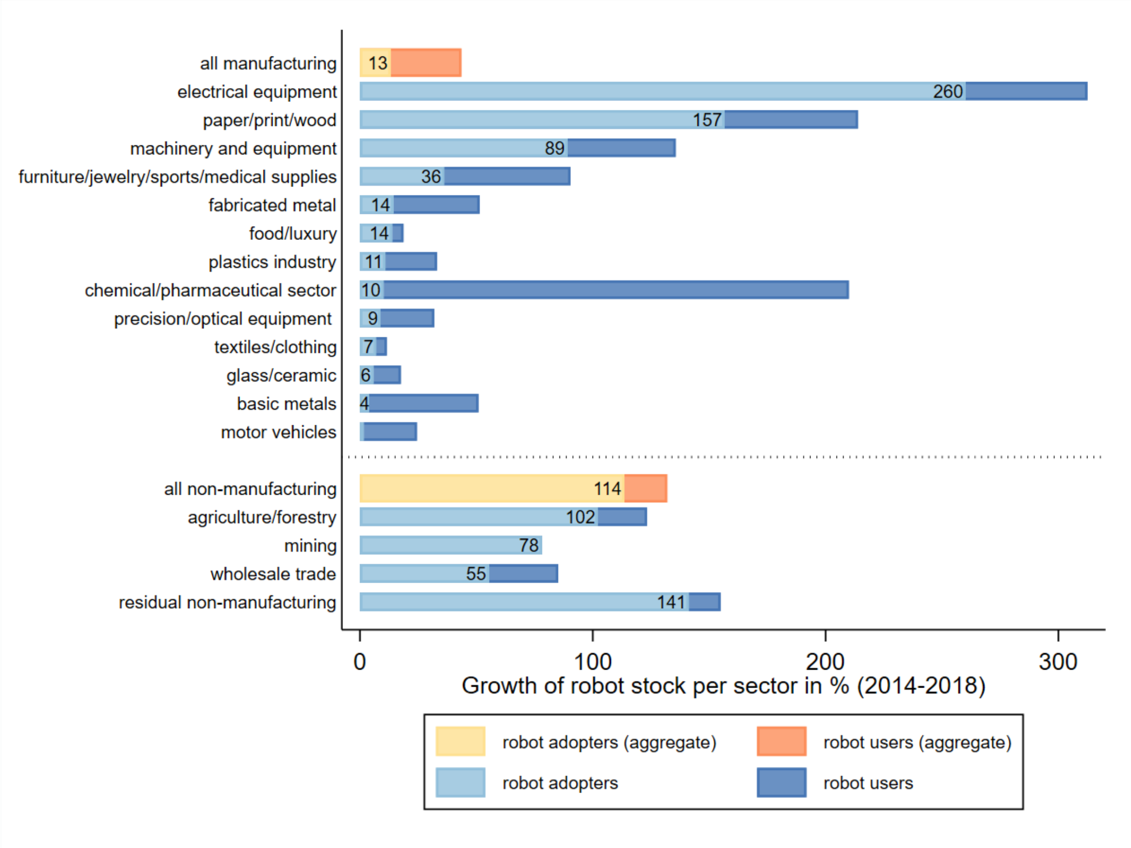

Figure 3: Decomposition of Growth of Robot Stock: The Extensive versus Intensive Margin

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 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.

Tables

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	N
Summary Statistics in 2018			
Employment	107.32	1100.12	15,307
Labor Productivity (€1,000/Worker)	56.79	69.39	8,267
log(TFP)	4.63	1.25	4,264
Exporter	0.22	0.41	13,156
Monthly Wage (€1,000)	2.07	2.14	12,386
Low-skilled Labor	0.34	0.30	15,307
Investment (€1,000)	1,410.24	52,105.62	14,282
Up-to-date Technology	0.62	0.48	15,262
Product Improvement	0.65	0.48	15,259
Process Improvement	0.83	0.38	15,259
Summary Statistics in 2014			
Employment	103.62	967.73	7,832
Business Volume (€1,000)	25,297.10	770,542.76	5,008
Labor Productivity (€1,000/Worker)	56.81	66.37	4,418
log(TFP)	4.47	1.28	3,840
Exporter	0.23	0.42	6,587
Monthly Wage (€1,000)	1.92	1.09	5,812
Low-skilled Labor	0.27	0.27	7832

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. TFP 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). Export is a dummy for exporter status. Monthly Wage is the average monthly wage of all employees that are subject to social insurance contributions, including part-time employees and apprentices. Low-skilled Labor is the share of workers without degree or apprenticeship in total employment. Investment is the total investment. Up-to-date Technology is a dummy variable for plants that answer "up to date" about their technological status. Product Improvement is a dummy variable for product improvement or refinement. Process improvement is a dummy variable for development or implementation of improved procedure. Business Volume is the total sales (CPI-deflated).

Table 2: The Extensive Margin: Share of Robot Users by Industry in 2018

Industry/Sector	Weighted (%)	Unweighted (%)	# of Surveyed 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
fabricated metal	6.22	17.07	457
machinery and equipment	11.29	15.90	434
electrical equipment	11.33	15.34	163
glass/ceramic	7.74	14.44	187
precision/optical equipment	4.16	11.18	152
paper/print/wood	7.61	10.96	228
food/luxury	5.87	10.54	313
furniture/jewelry/sports/medical	9.67	8.68	265
chemical/pharmaceutical	7.12	5.85	205
textiles/clothing	3.27	2.26	133
repair/installation	0.10	0.74	136
All Non-manufacturing	**0.94**	**1.16**	**12,050**
mining	5.71	12.00	25
agriculture/forestry	7.41	4.79	334
research/development	0.28	4.17	72
reparation of consumer goods	6.78	2.94	34
wholesale trade	1.62	2.51	479
retail trade	1.43	1.88	1,170
culture/sports/entertaining	2.00	1.71	175
legal accounting/advertising	1.46	1.38	290
building/installation	1.45	1.24	807
information/communication	0.43	1.24	322
architecture	0.34	1.22	328
other services	0.24	1.20	332
transport/warehousing	0.97	1.19	587
consulting	0.27	1.18	170
human health	0.34	1.04	1,828
main building sector	0.37	1.01	296
other non-manufacturing	0.28	0.49	4,937
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). (4) The second to last row is a residual category that consists of all the "other non-manufacturing" industries with the unweighted user share below 1%, which include itinerant trading/landscaping, repair/installation, activities of membership, civil service/social insurance, hotel business/gastronomy, energy, real estate activities, placement/temporary provision of labor, education, financial/insurance sector, sales/maintenance/repair of, marketing/design/translation, renting, and veterinary industry.

Table 3: Robotization Premia on the Extensive Margin

Dependent Variable	Employment	Labor Productivity	TFP	Exporter	Wage	Low-skilled Labor	Investment	Up-to-date Technology	Product Improvement	Process Improvement
No Control	1.802***	0.546***	-0.071	0.462***	0.449***	-0.070***	2.298***	0.045**	-0.353***	-0.308***
Full Sample	(0.070)	(0.035)	(0.053)	(0.020)	(0.024)	(0.010)	(0.105)	(0.019)	(0.019)	(0.020)
FE	1.422***	0.315***	-0.004	0.226***	0.246***	-0.030**	1.692***	0.122***	-0.246***	-0.254***
Full Sample	(0.064)	(0.041)	(0.023)	(0.016)	(0.031)	(0.012)	(0.101)	(0.021)	(0.020)	(0.016)
FE + Size		0.133***	-0.007	0.169***	0.006	0.027**	0.635***	0.096***	-0.163***	-0.197***
Full Sample		(0.040)	(0.024)	(0.016)	(0.028)	(0.012)	(0.076)	(0.021)	(0.020)	(0.016)
FE + Size		0.063	-0.007	0.074***	-0.026	0.051***	0.399***	0.076***	-0.103***	-0.145***
Manuf.		(0.041)	(0.023)	(0.024)	(0.027)	(0.012)	(0.085)	(0.027)	(0.025)	(0.023)
FE + Size		0.096	-0.012	0.081***	0.027	-0.044*	0.726***	0.118***	-0.177***	-0.215***
Non-manuf.		(0.088)	(0.060)	(0.027)	(0.057)	(0.023)	(0.150)	(0.040)	(0.038)	(0.029)

Notes: (1) The table reports 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, and Wage, Investment, are all in log values. Exporter, Update-to-date Technology, Product Improvement, and Process Improvement are dummy variables. Low-skilled Labor is the share of low-skilled labor in total employment. (4) There are five specifications. The first three specifications use the full sample (N=15,307). The fourth specification is based on the manufacturing sample (N=3,257) and the fifth is based on the non-manufacturing sample (N=12,050). The regression sample size varies across plant-level characteristics. (5) In the first specification (“No Control”), there is no additional control. The second specification (“FE”) includes industry (43 IAB aggregated NACE 2-digit industries) and state fixed effects. The last three specifications (“FE + Size”) include both fixed effects and plant-level employment (in log). (6) Robust standard errors are reported in parentheses. (6) *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Robotization Premia on the Intensive Margin

Dependent Variable	Employment	Labor Productivity	TFP	Exporter	Wage	Low-skilled Labor
		Controls: Industry and State Fixed Effects				
log(Robots)	0.393***	0.080***	-0.001	0.012	0.073***	0.005
	(0.049)	(0.028)	(0.016)	(0.016)	(0.018)	(0.009)
N	553	392	224	534	483	553
Adjusted R^2	0.436	0.263	0.891	0.291	0.424	0.174
		Controls: Industry and State Fixed Effects and Plant Size				
log(Robots)		0.023	0.002	-0.014	0.022	0.014
		(0.029)	(0.017)	(0.017)	(0.017)	(0.009)
N		392	224	534	483	553
Adjusted R^2		0.317	0.890	0.319	0.508	0.187

Notes: (1) The table reports the estimated coefficient of the number of robots (in log). (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. Low-skilled Labor is the share of low-skilled labor in total employment. (4) Both specifications are based on the full sample of robot users in 2018. The first specification includes industry (43 IAB aggregated NACE 2-digit industries) and state fixed effects. The second specification includes both fixed effects and plant-level employment (in log). (5) Robust standard errors are reported in parentheses. (6) *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Robotization Premia: Heterogeneity in Robot Types

	Employment	Labor Productivity	TFP	Exporter	Wage	Low-skilled Labor
			Extensive Margin			
Cage Robot User	0.935***	0.132*	-0.029	0.167***	0.014	0.007
	(0.121)	(0.072)	(0.043)	(0.029)	(0.052)	(0.022)
Expensive Robot User	0.719***	0.056	0.023	0.050	-0.020	0.036
	(0.129)	(0.077)	(0.046)	(0.031)	(0.055)	(0.024)
Other Robot User	0.697***	-0.144	-0.096	0.093**	0.071	0.012
	(0.160)	(0.097)	(0.061)	(0.038)	(0.067)	(0.029)
N	15,206	8,224	4,248	13,074	12,267	15,206
Adjusted R^2	0.228	0.250	0.935	0.303	0.356	0.211
			Intensive Margin			
log(Robots)	0.387***	0.031	-0.010	-0.015	0.024	0.018*
	(0.051)	(0.030)	(0.018)	(0.017)	(0.018)	(0.010)
Share of Cage Robots	0.551***	0.042	0.001	0.102**	-0.006	-0.004
	(0.158)	(0.092)	(0.063)	(0.052)	(0.054)	(0.028)
Share of Expensive Robots	0.440***	0.082	0.032	-0.014	0.014	0.038
	(0.139)	(0.080)	(0.049)	(0.045)	(0.048)	(0.025)
N	513	375	218	502	460	513
Adjusted R^2	0.459	0.327	0.889	0.334	0.494	0.201

Notes: (1) For the first panel, in 2018, 390 plants solely used cage robots (CageUser = 1), 323 plants solely used expensive robots (ExpUser = 1), and 107 plants were tagged as other robot users (OthUser = 1). 207 plants solely used both cage and expensive robots (CageUser = ExpUser = 1). Robot using plants that did not answer survey questions on robots types are excluded. (2) For the first panel, the control group are non robot using plants. (3) The dependent variables, Employment, Labor Productivity, TFP, and Wage, are all in log values. Exporter is a dummy variable. Low-skilled Labor is the share of low-skilled labor in total employment. (4) Column "Employment" includes only industry and state fixed effects; the other columns include both industry and state fixed effects and the employment count (in log) as controls. (5) No survey weights are applied. (6) Robust standard errors are reported in parentheses. (7) *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Correlates of Robot Adoption: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Sample	Full	Full	Full	Full	Full	Full	Full	Full	Full	Manuf.	Non-Manuf.
Employment	0.008***	0.011***	0.011***	0.008***	0.009***	0.0007***	0.008***	0.010***	0.010***	0.026***	0.003*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)	(0.002)
Labor Productivity		-0.000						-0.000	-0.002	-0.001	-0.003
		(0.003)						(0.003)	(0.003)	(0.010)	(0.002)
TFP			-0.006								
			(0.004)								
Low-skilled Labor				0.013**				0.021**	0.023**	0.047*	0.009
				(0.005)				(0.008)	(0.010)	(0.028)	(0.008)
Wage					-0.003						
					(0.003)						
Minimum Wage						0.004		0.007	0.008	0.027**	-0.001
						(0.003)		(0.005)	(0.005)	(0.014)	(0.004)
Exporter							0.026***	0.030***	0.029***	0.030**	0.015***
							(0.004)	(0.006)	(0.006)	(0.014)	(0.006)
Other controls	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,629	4,269	3,694	7.629	5,628	7,414	6,391	4,244	3,747	1,178	2,569
Adjusted R^2	0.042	0.038	0.039	0.043	0.041	0.042	0.047	0.045	0.050	0.066	0.006

Notes: (1) The table reports OLS regression results for robot adoption. (2) No survey weights are applied. (3) The independent variables, Employment, Labor Productivity, TFP, and Wage, are all in log values. Minimum Wage is a dummy variable which equals one if the plant raised wages due to the minimum wage regulation in 2015. Exporter is a dummy variable. Low-skilled Labor is the share of low-skilled labor in total employment. (4) Other controls are a set of dummy variables for up-to-date technology, labor scarcity, collective wage agreement, process improvement, works council, high competitive pressure, and foreign ownership. (5) Both industry (43 IAB aggregated NACE 2-digit industries) and state fixed effects are included. (6) Robust standard errors are reported in parentheses. (7) *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Correlates of Robot Adoption: Alternative Firm Size Control

	(1)	(2)	(3)	(4)
Sample	Full	Full	Manuf.	Non-Manuf.
Business Volume	0.009***	0.009***	0.024***	0.003**
	(0.001)	(0.002)	(0.005)	(0.002)
Labor Productivity	-0.007**	-0.008**	-0.017	-0.005*
	(0.003)	(0.004)	(0.011)	(0.003)
Low-skilled Labor	0.023***	0.024**	0.051*	0.010
	(0.008)	(0.010)	(0.028)	(0.008)
Minimum Wage	0.008*	0.008	0.029**	-0.001
	(0.005)	(0.005)	(0.014)	(0.004)
Exporter	0.028***	0.027***	0.028**	0.014**
	(0.006)	(0.006)	(0.014)	(0.006)
Other controls	No	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	4,244	3,747	1,178	2,569
Adjusted R^2	0.046	0.051	0.067	0.007

Notes: (1) The table reports OLS regression results for robot adoption. (2) No survey weights are applied. (3) The independent variables, Business Volume and Labor Productivity, are all in log values. Minimum Wage is a dummy variable which equals one if the plant raised wages due to the minimum wage regulation in 2015. Exporter is a dummy variable. Low-skilled Labor is the share of low-skilled labor in total employment. (4) Other controls are a set of dummy variables for up-to-date technology, labor scarcity, collective wage agreement, process improvement, works council, high competitive pressure, and foreign ownership. (5) Both industry (43 IAB aggregated NACE 2-digit industries) and state fixed effects are included. (6) Robust standard errors are reported in parentheses. (7) *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Correlates of Robot Adoption: The Panel Sample

	(1)	(2)	(3)	(4)
Sample	Full	Full	Manuf.	Non-Manuf.
Employment	0.005***	0.004***	0.012***	0.001*
	(0.001)	(0.001)	(0.004)	(0.001)
Labor Productivity	0.001	-0.000	0.002	-0.001
	(0.001)	(0.002)	(0.006)	(0.001)
Low-skilled Labor	0.007	0.009*	0.032**	-0.001
	(0.004)	(0.005)	(0.015)	(0.004)
Minimum Wage	0.004	0.004	0.015*	-0.001
	(0.003)	(0.003)	(0.008)	(0.002)
Exporter	0.014***	0.014***	0.018***	0.003
	(0.003)	(0.003)	(0.006)	(0.003)
Other controls	No	Yes	Yes	Yes
Industry-period FE	Yes	Yes	Yes	Yes
State-period FE	Yes	Yes	Yes	Yes
N	8,228	7,498	2,333	5,165
Adjusted R^2	0.273	0.279	0.308	0.193

Notes: (1) The table reports the regression results for robot adoption, repeated for 2 periods of robot adoption. Explanatory variables for the first period of adoption are from base year 2014, while for the second period of adoption the base year is 2016. (2) No survey weights are applied. (3) The independent variables, Employment and Labor Productivity, are all in log values. Minimum Wage is a dummy variable which equals one if the plant raised wages due to the minimum wage regulation in 2015. Exporter is a dummy variable. Low-skilled Labor is the share of low-skilled labor in total employment. (4) Other controls are a set of dummy variables for up-to-date technology, labor scarcity, collective wage agreement, process improvement, works council, high competitive pressure, and foreign ownership in the base year. (5) Standard errors clustered at the plant level are reported in parentheses. (6) *** p<0.01, ** p<0.05, * p<0.1.

A Appendix

A.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 axis 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 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?

A.2 Cross Validation and Stylized Facts: Additional Figures

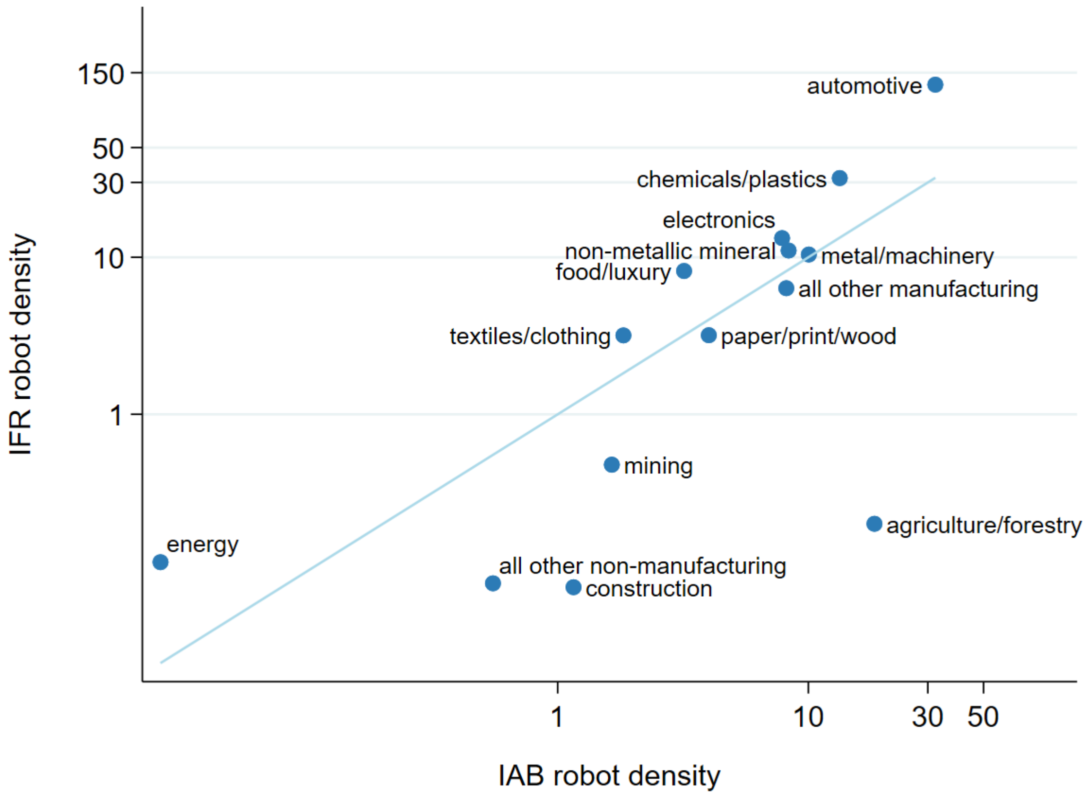

Figure A1: Cross Validation with the IFR Data in 2018

Notes: (1) Robot density is defined as the number of robots per 1,000 employees. (2) Robot counts in 2018 are aggregated at industry level and divided by the aggregate number of employees per industry to obtain IAB robot density. As the IAB Establishment Panel is representative on industry level, we use the same employment count to derive IFR robot density. (3) The correlation coefficient of robot density across industries between the two datasets is 0.84. If only the manufacturing industries are considered, the correlation coefficient is 0.96.

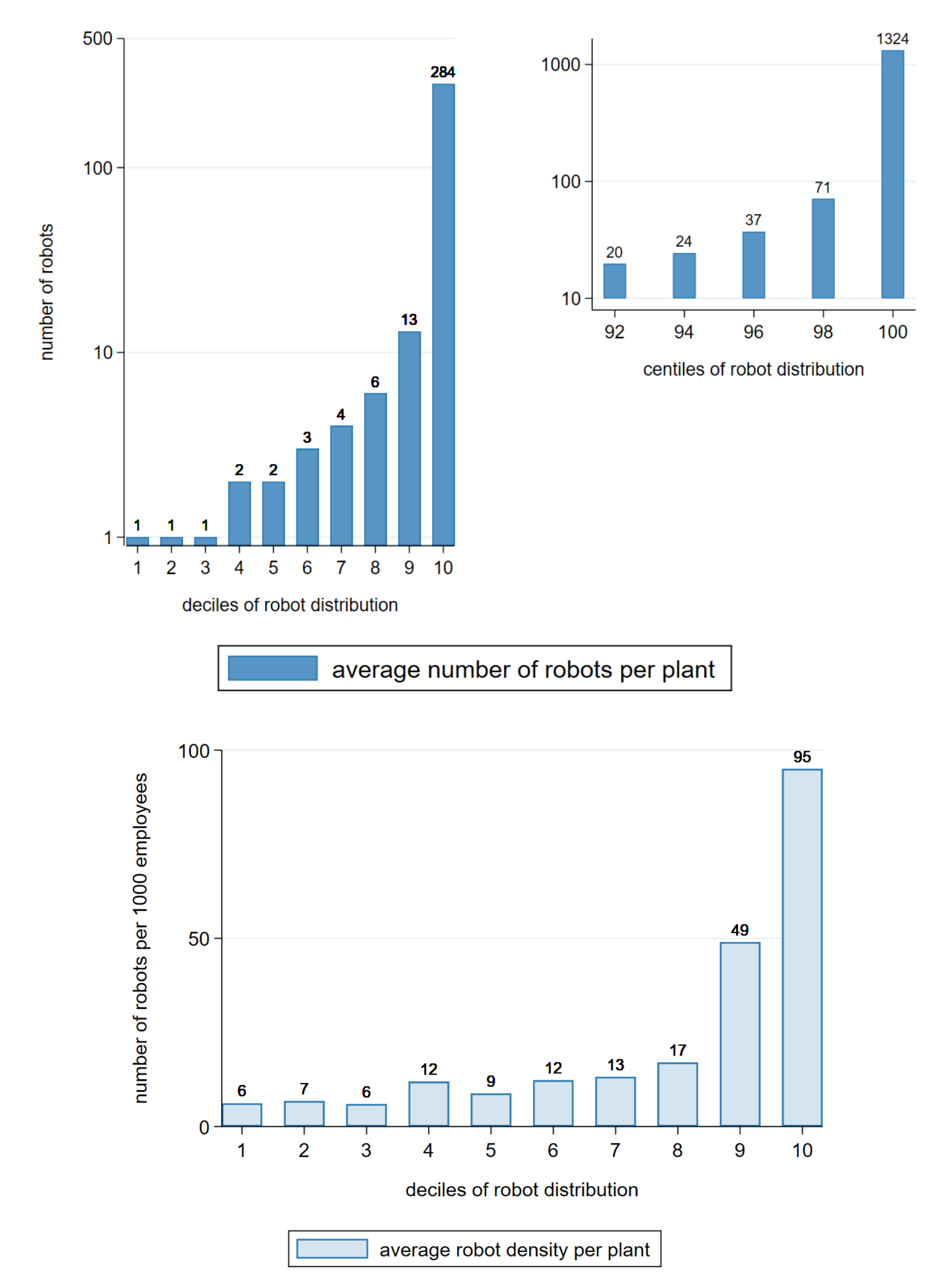

Figure A2: Robot Distribution in the Manufacturing Sector in 2018 (without Survey Weights)

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 skewedness of the distribution, the first panel is plotted in log scale.

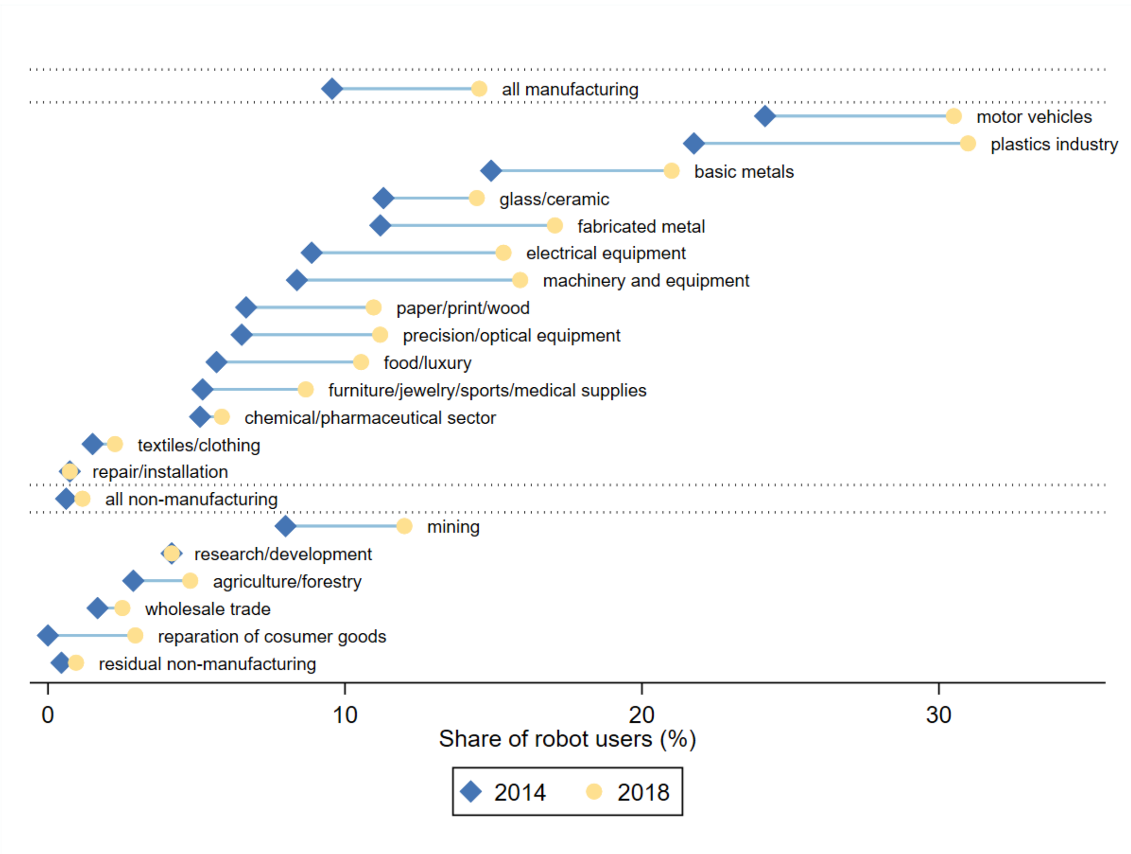

Figure A3: Growth in the Extensive Margin from 2014 to 2018

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.

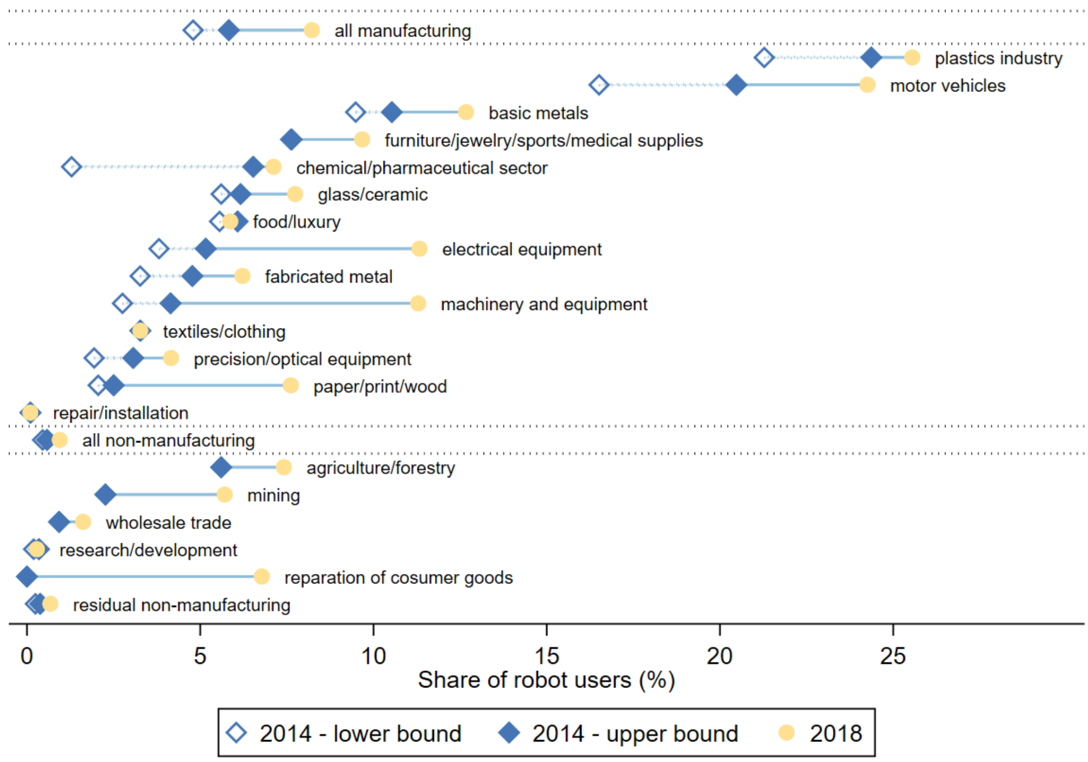

Figure A4: Growth in the Extensive Margin from 2014 to 2018: Lower and Upper Bounds

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.

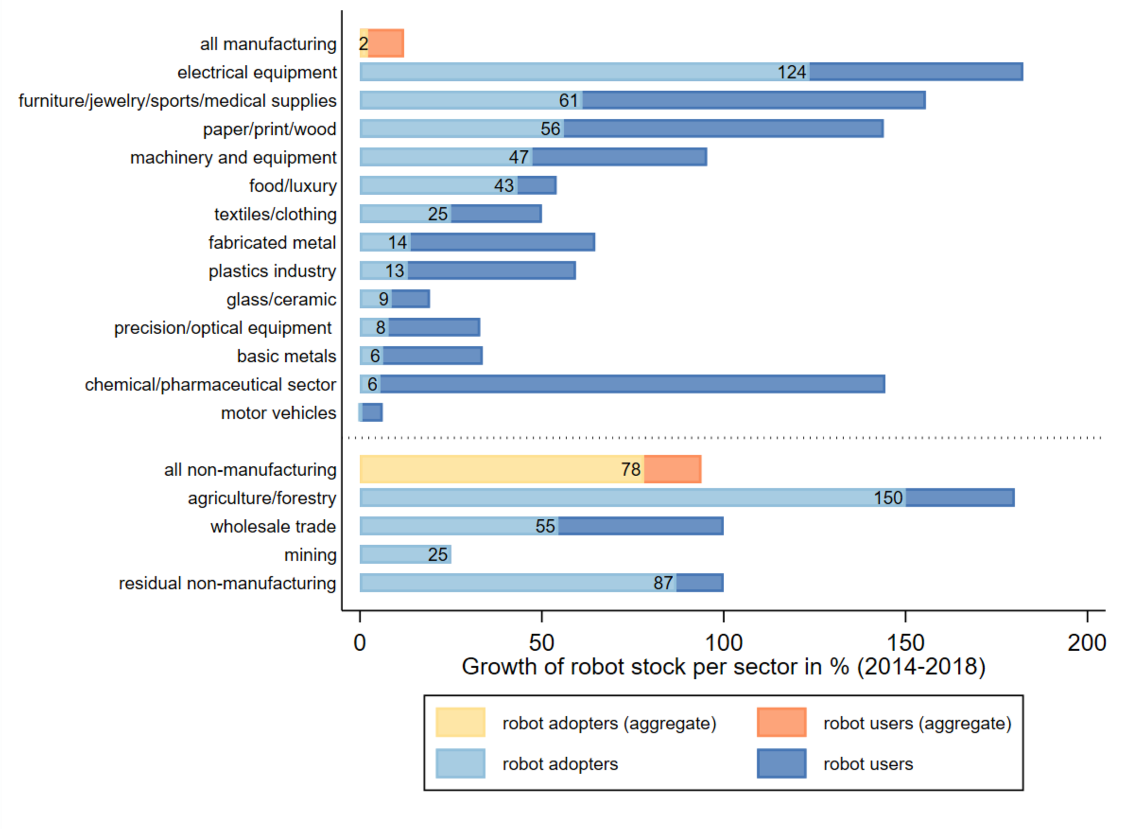

Figure A5: Decomposition of Growth of Robot Stock (without Survey Weights)

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.

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