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**Article**

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# Robot Adoption at German Plants

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**Abstract:** Using a newly collected dataset at the plant level from 2014 to 2018, we provide the first microscopic portrait of robotization in Germany and study the correlates of robot adoption. Our descriptive analysis uncovers five stylized facts: (1) Robot use is relatively rare. (2) The distribution of robots is highly skewed. (3) New robot adopters contribute substantially to the recent robotization. (4) Robot users are exceptional. (5) Heterogeneity in robot types matters. Our regression results further suggest plant size, high-skilled labor share, exporter status, and labor shortage to be strongly associated with the future probability of robot adoption.

**Keywords:** Robots; robot adoption; automation; labor; productivity; plant-level

**JEL Classification:** J24; O14; O33

## 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

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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 micro-economic 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.<sup>1</sup> 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.<sup>2</sup> Second, the distribution of robots is highly skewed. Top 5 % of the robot-using plants, in terms 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.<sup>3</sup> 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

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<sup>1</sup> 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.

<sup>2</sup> See IFR's Annual Report, *World Robotics: Industrial Robots 2018*.

<sup>3</sup> All the results reported in this paper are correlational findings.

manufacturing plants that raise wages due to the minimum wage regulation are associated with a higher likelihood of robot adoption.<sup>4</sup> 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.

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, Manuylov, and Smolka (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, Lo Turco, and Martínez-Zarzoso (2022) provide robust evidence of a positive effect of robot adoption on export performance.<sup>5</sup> 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, Lelarge, and Pascual (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.<sup>6</sup> We focus on Germany. Because of Germany's high robot density and its leading role in robot production, our analysis thus provides a microscopic

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4 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, Wittbrodt, and Schröder (2019).

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

6 Also see Cheng et al. (2019) for a survey of Chinese firms with robot-related questions, Barth et al. (2020) and Dixon, Hong, and Wu (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, Stenhammar, and Tuhkuri 2022).

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.<sup>7</sup>

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 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, Manuylov, and Smolka (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, Hu, and Tang (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.<sup>8</sup> 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

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<sup>7</sup> After the working paper version of this paper was published (Deng, Plümpe, and Stegmaier 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.

<sup>8</sup> For further evidence on the labor market effects of robots in Europe, see Chiacchio, Petropoulos, and Pichler (2018) and Klenert, Fernandez-Macias, and Antón (2023). Borjas and Freeman (2019) compare the robot shock and the immigrant shock in the context of the US labor market. Stiebale, Suedekum, and Woessner (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, Bastos, and Rijkers (2020), Faber (2020), Furusawa, Kusaka, and Sugita (2022), and Krenz, Prettnner, and Strulik (2021).

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 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.

## 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.<sup>9</sup> 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.<sup>10</sup> The resulting plant-level data on robots is of high quality<sup>11</sup> and the distribution across industries is highly correlated with the industry-level IFR data for Germany (Plümpe and Stegmaier 2022).

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, Lelarge, and Pascual 2020;

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<sup>9</sup> 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).

<sup>10</sup> An English translation of the survey questions can be found in the Appendix.

<sup>11</sup> For more details on data quality, consistency checks, and data cleaning, see Plümpe and Stegmaier (2022).

Barth et al. 2020; Bonfiglioli et al. 2019; Humlum 2019).<sup>12</sup> 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, Manuylov, and Smolka (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 reports the summary statistics for the main non-robot variables in 2014 and 2018. The sample size is larger in 2018 because of the survey attrition when constructing our sample retrospectively based on the 2019 surveyed plants.

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,

Table 1: Summary statistics.

Variable	Year 2018			Year 2014		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
log (Employment)	2.93	1.68	15,307	3.02	1.60	7852
log (Labor productivity)	10.63	0.84	8267	10.57	0.86	4945
log (TFP)	4.65	1.25	4264	4.48	1.30	4262
log (Wage)	7.38	0.68	8563	7.38	0.66	5542
High-skilled labor	0.09	0.19	11,470	0.09	0.19	6942
Exporter	0.22	0.41	12,912	0.23	0.42	6533

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 €1000/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, calculated 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.

12 Acemoglu, Lelarge, and Pascual (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.

survey weights are applied to obtain representative results for Germany.<sup>13</sup> 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 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.<sup>14</sup> 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. 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.

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,

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**13** We focus on the results with survey weights in the main text and relegate some of the unweighted results to the Appendix.

**14** In Table 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.



**Table 2:** The extensive margin: Share of robot users by industry in 2018.

Industry/sector	Weighted (%)	Unweighted (%)	# of plants
<b>All manufacturing</b>	<b>8.22</b>	<b>14.52</b>	<b>3257</b>
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
<b>All non-manufacturing</b>	<b>0.94</b>	<b>1.16</b>	<b>12,050</b>
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
<b>Total</b>	<b>1.55</b>	<b>4.00</b>	<b>15,307</b>

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 *other 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.

1991, and 1993, Dinlersoz and Wolf (2018) document a larger share of plants used robots for five manufacturing industries.<sup>15</sup> 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 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

<sup>15</sup> 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.

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, 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.<sup>16</sup> Based on the same sorting of plants, the second panel of Figure 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 1000 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.<sup>17</sup>

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.

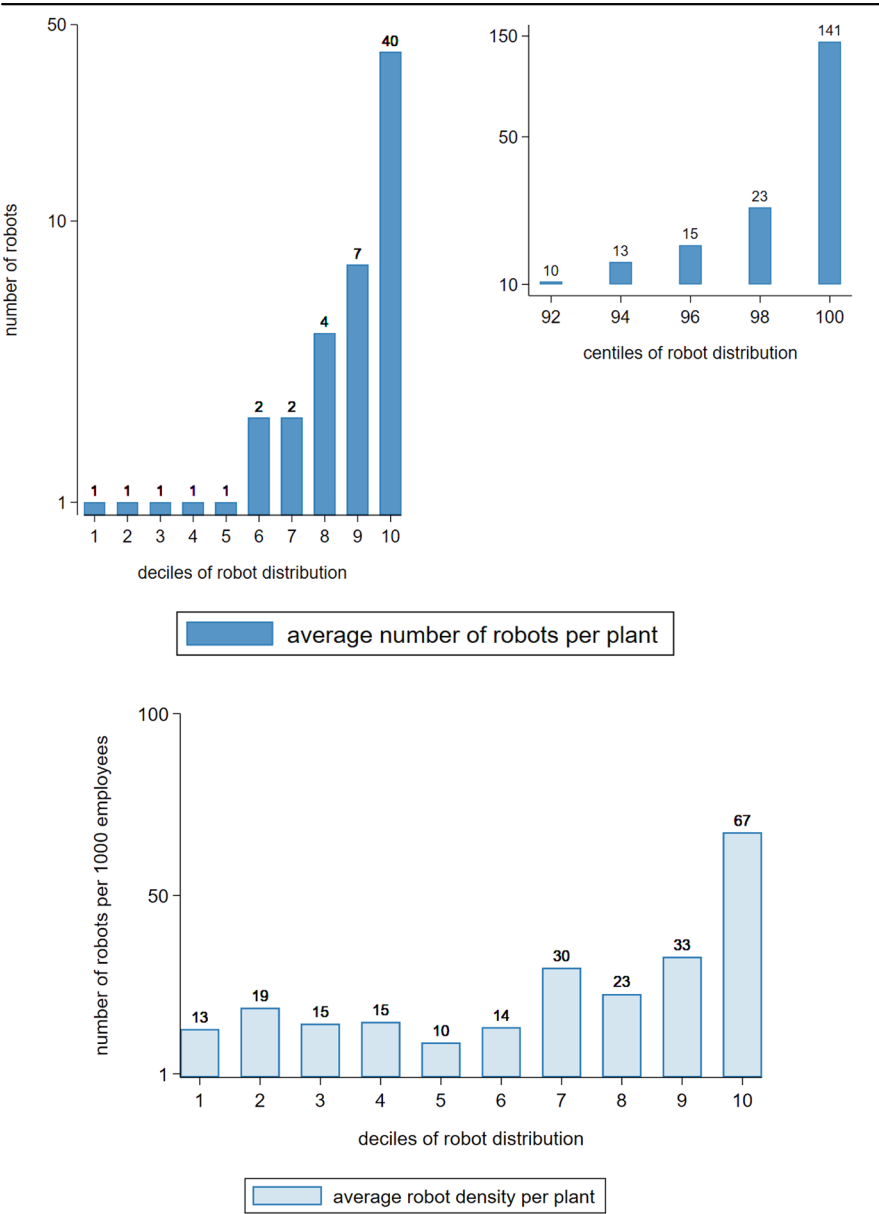
**Fact III: The extensive margin contributes substantially to robotization.** Robot adopters, the plants that newly adopted robots from 2014 to 2018, make a substantial contribution to the growth in both the share of robot users and the total robot stock. In our survey sample, 184 plants, around 30 % of all the robot users in 2018, report that they newly adopted robots during the period from 2014 to 2018. Figure 2 compares across industries the share of robot users in 2014 with that in 2018.<sup>18</sup> The

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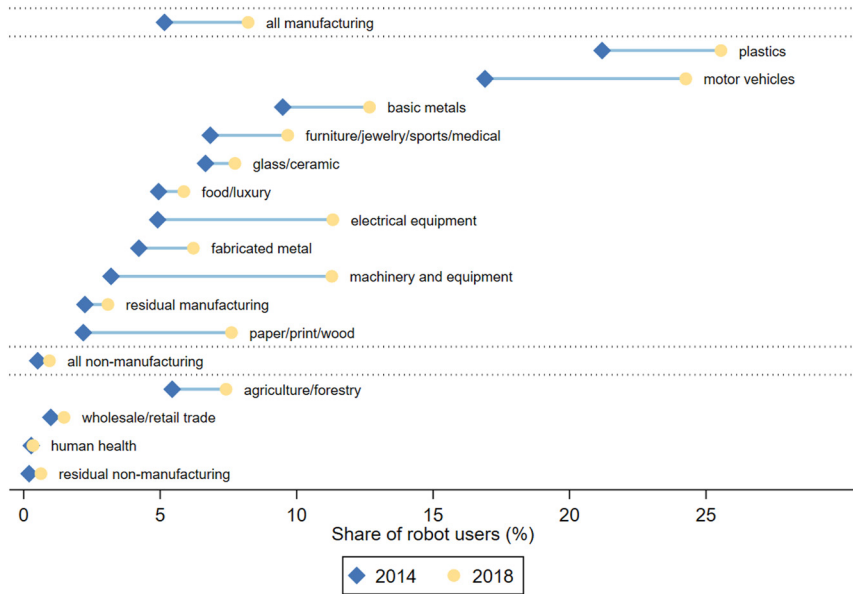
<sup>16</sup> Without survey weights the robot distribution is even more skewed, as shown in Figure A1 in the Appendix.

<sup>17</sup> 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.

<sup>18</sup> We use the 2018 survey weights to calculate the user shares in 2014 and 2018 in Figure 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



**Figure 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 1000 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 on log scale.



**Figure 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.

share of robot users in the manufacturing sector increases by more than 50 % from 5.16 % to 8.22 %.<sup>19</sup> 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 %.<sup>20</sup> Moreover, divestment in

not have fully representative data for earlier years. Without survey weights the pattern remains qualitatively the same, as depicted in Figure A2 in the Appendix.

<sup>19</sup> 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.

<sup>20</sup> It should be noted that out of the 616 plants that report using robots from 2014 to 2018 in our survey sample, 99 ( $\approx 16\%$ ) 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 A3 in the

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 3 plots the growth of robot stock by industry from 2014 to 2018.<sup>21</sup> 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 % points are contributed by new adopters; In the non-manufacturing sector, robot stock in total increases by 132 % and 114 % 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 % 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 2.<sup>22</sup>

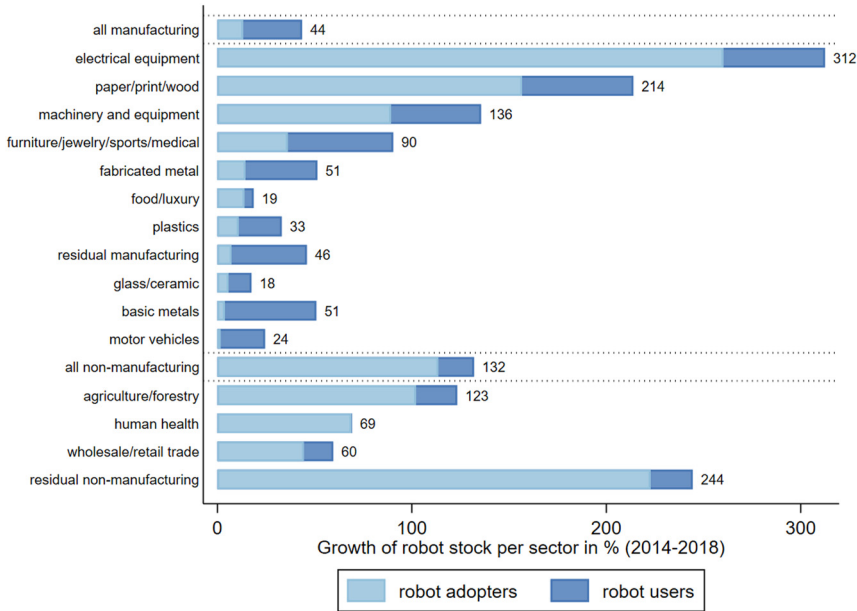
Our findings, taken together, point to the importance of the extensive margin. It indicates that the recent wave of robotization is not only a process of capital deepening for the existing users but also a classic example of technology diffusion, as more and more plants reap the benefits of the new automation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

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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.

<sup>21</sup> For the decomposition without survey weights, see Figure A4 in the Appendix.

<sup>22</sup> 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 formally modeled in Humlum (2019) and also extensively discussed in the earlier literature on vintage capital models (Benhabib and Rustichini 1991; Boucekkine, Germain, and Licandro 1997).



**Figure 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.

**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,<sup>23</sup> that is, how robot users differ from non-users in a wide array of plant-level characteristics, we use the 2018 cross-sectional sample to perform the following bivariate regressions:

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

<sup>23</sup> This term, “robotization premia”, is meant to draw a direct parallelism with the exporter premia as in Bernard et al. (2007) and Bernard et al. (2018).

where  $X_{ijk}$  is a given characteristic of interest for plant  $i$  in industry  $j$  and state  $k$ ;  $\text{RobotUse}_{ijk}$  is a dummy variable which equals one if plant  $i$  used robots in 2018 and zero otherwise;  $\phi_j$  and  $\psi_k$  are the industry and state fixed effects;  $\text{Emp}_{ijk}$  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.<sup>24</sup> 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 3 presents the estimates of  $\beta$  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 3 because the fraction of missing values varies with the plant-level characteristics.<sup>25</sup>

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 % points higher for robot users. According to Column (7), the probability of adopting up-to-date or relatively up-to-date technology

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<sup>24</sup> For a detailed comparison between weighted regressions and unweighted regressions with the elements of the survey design being controlled for, see Bossler, Geis, and Stegmaier (2018).

<sup>25</sup> To ensure that our results are not driven by sample selection, we rerun all the specifications in Tables 3–5 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 3: Robotization premia: the extensive margin.

	Dependent variable									
	Employment (1)	Labor productivity (2)	TFP (3)	High-skilled labor (4)	Wage (5)	Exporter (6)	Up-to-date technology (7)	Product improvement (8)	Process improvement (9)	Investment (10)
None	1.783*** (0.162)	0.551*** (0.062)	-0.082 (0.134)	0.003 (0.013)	0.408*** (0.061)	0.462*** (0.037)	0.032 (0.030)	0.347*** (0.024)	0.305*** (0.025)	2.289*** (0.218)
FE	1.418*** (0.122)	0.306*** (0.043)	0.093* (0.049)	0.020*** (0.007)	0.216*** (0.040)	0.228*** (0.026)	0.117*** (0.025)	0.237*** (0.020)	0.250*** (0.022)	1.657*** (0.158)
FE + size		0.123*** (0.042)	0.087* (0.053)	-0.009 (0.008)	-0.018 (0.036)	0.168*** (0.025)	0.086*** (0.026)	0.152*** (0.020)	0.191*** (0.022)	0.600*** (0.097)
FE + size Manuf.		0.055 (0.042)	0.041 (0.035)	-0.019*** (0.006)	-0.043 (0.026)	0.072*** (0.026)	0.060* (0.032)	0.091*** (0.023)	0.140*** (0.028)	0.383*** (0.094)
FE + size Non-manuf.		0.095 (0.083)	0.237* (0.142)	0.018 (0.018)	-0.079 (0.105)	0.090** (0.040)	0.139*** (0.042)	0.173*** (0.039)	0.215*** (0.048)	0.706*** (0.196)

Notes: (1) The table reports OLS regression results of Equation (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 ( $N = 3068$ ) 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), 7671 for (2), 3974 for (3), 10,440 for (4), 7807 for (5), 11,933 for (6), 10,142 for (7), 14,174 for (8), 14,177 for (9), and 8167 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) \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .



increases by 8.6 % points for robot users.<sup>26</sup> 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 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,<sup>27</sup> 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 manufacturing sector, the share of high-skilled labor (employees with a university degree), with the plant size being controlled for, is 1.9 % 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.<sup>28</sup>

**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 53 % 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, 94 % of them have all of their robots operated

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<sup>26</sup> 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.

<sup>27</sup> 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.

<sup>28</sup> In the Appendix, we also report the robotization premia on the intensive margin within the sample of robot users.

in separation from employees, accounting for 72 % of the total robot stock. Among those expensive robot users, 80 % of them have all of their robots purchased at a price above 50,000 Euros, accounting for 45 % of the total robot stock.<sup>29</sup>

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

$$X_{ijk} = \alpha + \beta_1 \text{RobotUse}_{ijk} + \beta_2 \text{RobotUse}_{ijk} \times \text{Cage}_{ijk} + \beta_3 \text{RobotUse}_{ijk} \times \text{Expensive}_{ijk} + \phi_j + \psi_k + \gamma \log(\text{Emp}_{ijk}) + \varepsilon_{ijk}, \quad (2)$$

where  $\text{RobotUse}_{ijk}$  is the dummy of whether a plant is a robot user as we have defined before,  $\text{Cage}_{ijk}$  is a dummy variable that equals one if a robot user has its *all* robots being cage robots, and  $\text{Expensive}_{ijk}$  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 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 labor (Column (4)) and enjoy a much higher premium in the probability to export (Column (6)).<sup>30</sup>

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.

<sup>29</sup> These shares are calculated with survey weights. Within the survey sample, close to 69 % of the robot users use cage robots and 62 % of them use expensive robots.

<sup>30</sup> 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 4 using the restricted sample as described in Footnote 25. 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,  $\text{RobotUse}$  is no longer significant.

**Table 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*** (0.188)	−0.025 (0.074)	0.117 (0.125)	0.015 (0.018)	0.009 (0.059)	0.081** (0.036)
RobotUse × Cage	0.383** (0.163)	0.116 (0.075)	−0.094 (0.103)	−0.035** (0.016)	−0.005 (0.050)	0.099** (0.044)
RobotUse × Expensive	0.440** (0.193)	0.092 (0.060)	0.052 (0.085)	0.007 (0.013)	−0.034 (0.049)	0.031 (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	7630	3,960	10,391	7,786	11,861
Adjusted R <sup>2</sup>	0.271	0.282	0.798	0.281	0.423	0.309

Notes: (1) This table reports the OLS regression results for Equation (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) \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

### 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.<sup>31</sup> Our baseline cross-sectional specification is given by

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

<sup>31</sup> 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’.

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 not use robots in 2014 newly adopted robots from 2015 to 2018 and zero otherwise;  $\phi_j$  and  $\psi_k$  are the industry and state fixed effects. Based on our definition of robot adoption, 184 plants in total are identified as robot adopters from 2015 to 2018, among which 32 adopted robots for the first time in 2015, 42 in 2016, 33 in 2017, and 77 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, Manuylov, and Smolka 2021). Assuming the fixed cost of robot adoption, Koch, Manuylov, and Smolka (2021) demonstrate 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 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.<sup>32</sup> In Columns (3)–(8), we include employment as a plant size control. Plant size always enters the regression significantly with a positive sign. 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

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<sup>32</sup> 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, Klenert, and Anton 2021).

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, Manuylov, and Smolka (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 5, albeit intriguing, may be viewed as inconclusive given its parsimonious specification. Table 6 then presents the regression results for specifications in which we include simultaneously all the main correlates of robot adoption.<sup>33</sup> 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,<sup>34</sup> 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 %-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 %-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 % 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.

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<sup>33</sup> 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.

<sup>34</sup> These additional controls are dummies for works council, technological status, process improvement, degree of competition, and foreign ownership.

Table 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*** (0.002)	0.013*** (0.003)	0.009*** (0.002)	0.010*** (0.002)	0.008*** (0.002)	0.009*** (0.002)	0.011*** (0.002)	0.008*** (0.002)	0.009*** (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	4242	6822	3803	5978	4776	6610	5616	4731	5849	5849
Adjusted R <sup>2</sup>	0.028	0.043	0.041	0.042	0.043	0.042	0.047	0.042	0.042	0.042

Columns (3)–(6) in Table 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. 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. 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, Hu, and Tang (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.

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*Notes:* (1) The table reports the OLS regression results for Equation (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) \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table 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*** (0.002)	0.008*** (0.002)	0.032*** (0.007)	0.024*** (0.007)	0.003*** (0.001)	0.002 (0.002)
High-skilled labor	−0.025* (0.013)	−0.030* (0.016)	−0.139*** (0.043)	−0.137*** (0.044)	0.003 (0.011)	0.003 (0.015)
Minimum wage	0.004 (0.005)	0.008 (0.006)	0.016 (0.016)	0.030* (0.016)	−0.000 (0.004)	−0.002 (0.004)
Exporter	0.032*** (0.007)	0.030*** (0.006)	0.037*** (0.013)	0.037*** (0.012)	0.014** (0.006)	0.014** (0.006)
Demand for training	0.016** (0.008)	0.016* (0.008)	0.038* (0.022)	0.032 (0.022)	0.008 (0.006)	0.010 (0.007)
Skilled labor shortage	−0.010** (0.005)	−0.008 (0.005)	−0.009 (0.013)	−0.003 (0.014)	−0.009*** (0.003)	−0.008** (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
<i>N</i>	4698	4241	1294	1231	3404	3010
Adjusted <i>R</i> <sup>2</sup>	0.064	0.070	0.098	0.102	0.024	0.031

Notes: (1) The table reports the OLS regression results for Equation (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) \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

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

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

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 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  $\phi_{jt}$  and  $\psi_{kt}$  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 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 6, the point estimates for the total employment, the share of high-skilled labor, and exporter status are about

**Table 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*** (0.001)	0.004*** (0.001)	0.017*** (0.003)	0.012*** (0.003)	0.001** (0.001)	0.001* (0.001)
High-skilled labor	−0.013*** (0.005)	−0.016*** (0.006)	−0.074*** (0.021)	−0.074*** (0.022)	0.001 (0.004)	0.001 (0.005)
Minimum wage	0.002 (0.003)	0.004 (0.003)	0.008 (0.007)	0.015** (0.007)	−0.000 (0.002)	−0.001 (0.002)
Exporter	0.016*** (0.003)	0.015*** (0.004)	0.017*** (0.007)	0.017*** (0.007)	0.007* (0.004)	0.007* (0.004)
Demand for training	0.008* (0.004)	0.008* (0.004)	0.019 (0.013)	0.017 (0.013)	0.004 (0.003)	0.005 (0.003)
Skilled labor shortage	−0.005** (0.002)	−0.004* (0.002)	−0.006 (0.007)	−0.003 (0.007)	−0.004** (0.002)	−0.004** (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	9181	2814	2689	7306	6492
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 (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) \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

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.

## 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.

## 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 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?

## A.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), the following regression specification:

$$X_{ijk} = \alpha + \beta \log(\text{Robot}_{ijk}) + \phi_j + \psi_k + \gamma \log(\text{Emp}_{ijk}) + \varepsilon_{ijk}, \quad (5)$$

where  $\log(\text{Robot})$  is the log number of robots in a given plant in 2018.

Table A1 reports the estimates of  $\beta$  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

**Table A1:** Robotization premia: The intensive Margin

	Dependent variable					
	Employment (1)	Labor productivity (2)	TFP (3)	High-skilled labor (4)	Wage (5)	Exporter (6)
log (Robots)	0.396*** (0.082)	0.073*** (0.028)	−0.039 (0.031)	0.005 (0.005)	0.067*** (0.018)	0.013 (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 <sup>2</sup>	0.437	0.320	0.375	0.335	0.458	0.311
log (Robots)			−0.022 (0.037)	−0.001 (0.005)	0.012 (0.014)	−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 <sup>2</sup>	0.437	0.376	0.375	0.357	0.552	0.341

Notes: (1) The table reports the OLS regression results for Equation (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 A2:** 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*** (0.091)	0.019 (0.027)	−0.016 (0.043)	−0.002 (0.005)	0.008 (0.016)	−0.014 (0.020)
Share of cage robots	0.602*** (0.163)	0.013 (0.105)	−0.043 (0.185)	−0.020 (0.020)	0.011 (0.077)	0.119** (0.055)
Share of expensive robots	0.451** (0.180)	0.030 (0.063)	0.018 (0.126)	−0.007 (0.018)	−0.048 (0.056)	0.005 (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 <sup>2</sup>	0.460	0.389	0.357	0.361	0.534	0.344

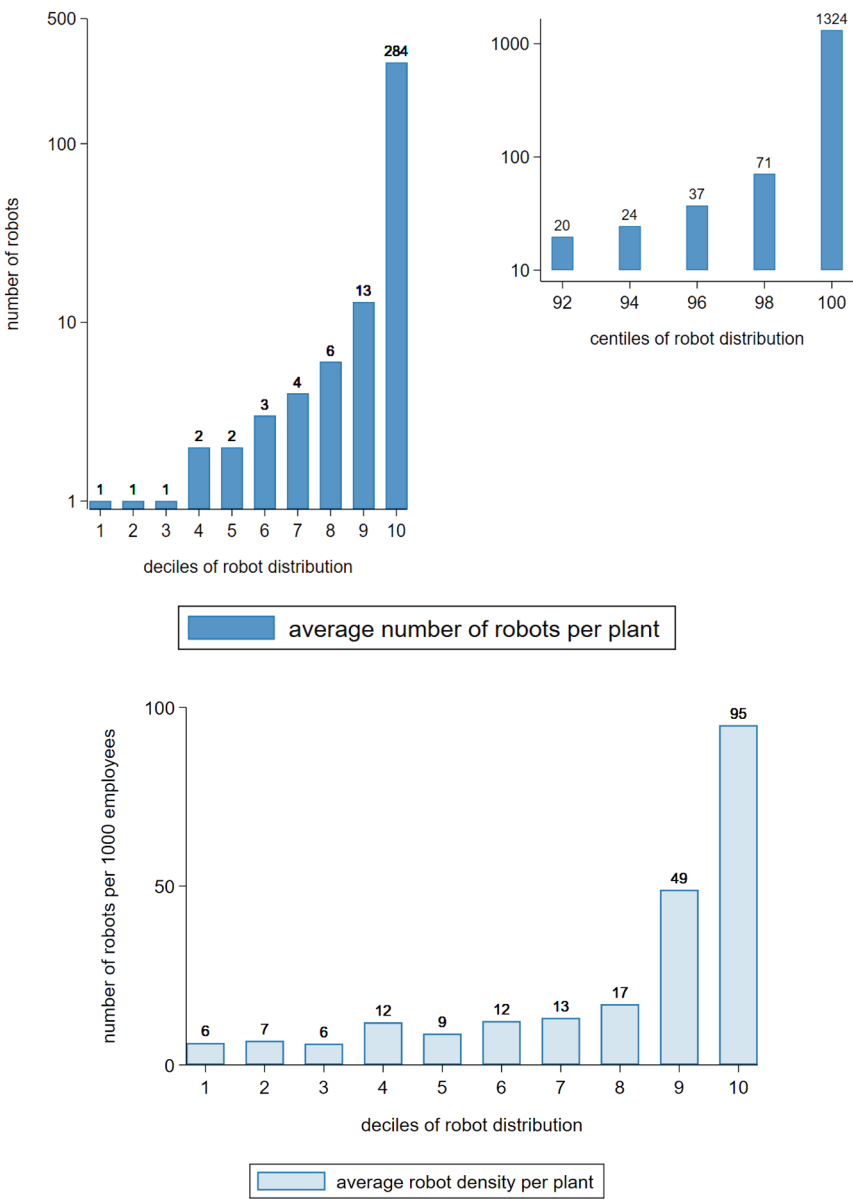
Notes: (1) This table reports the OLS regression results for Equation (5) with the share of different types of robots being incorporated. (2) No survey weights are applied. (3) The dependent variables, Employment, Labor productivity, TFP, and Wage, are all in log values. Exporter is a dummy variable. 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) \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

regression results are inconclusive. We do not find strong evidence of differences in plant-level characteristics other than employment between different robot users.

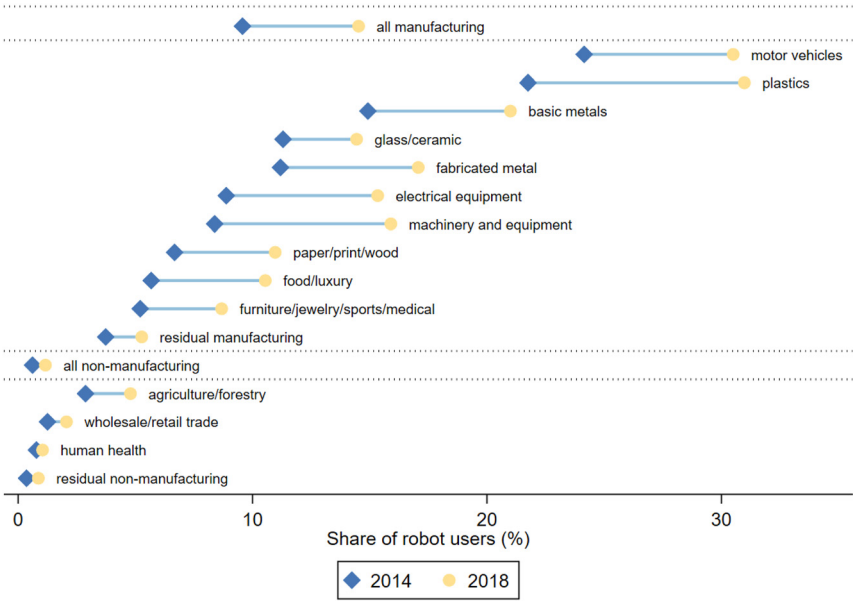
Moreover, to study the role of robot heterogeneity in the intensive margin, we incorporate into Equation (5) the share of cage robots and the share of expensive robots and report the estimation results based on the sample of robot users in Table A2. The two new variables enter the regression positively 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.

### A.3 Additional Figures

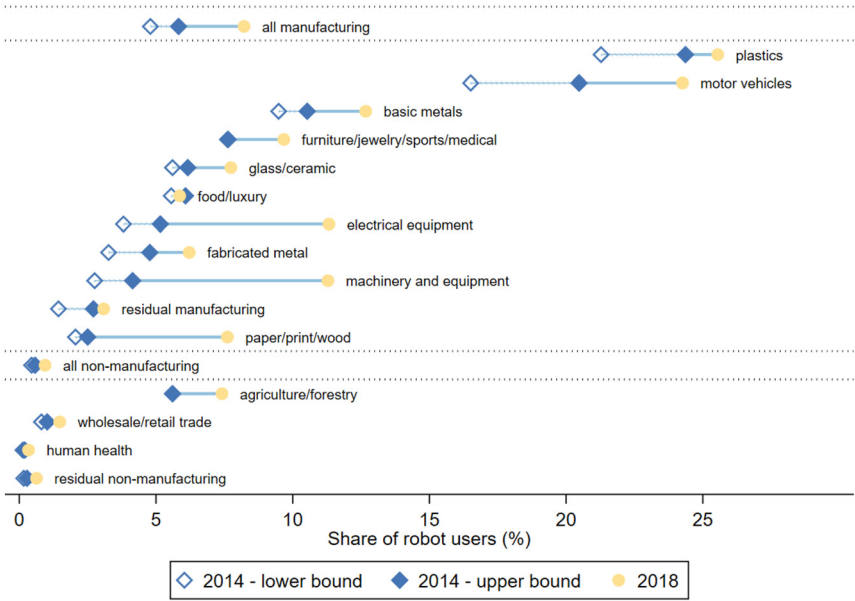
See Figures A1–A4



**Figure A1:** 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 1000 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 on log scale.

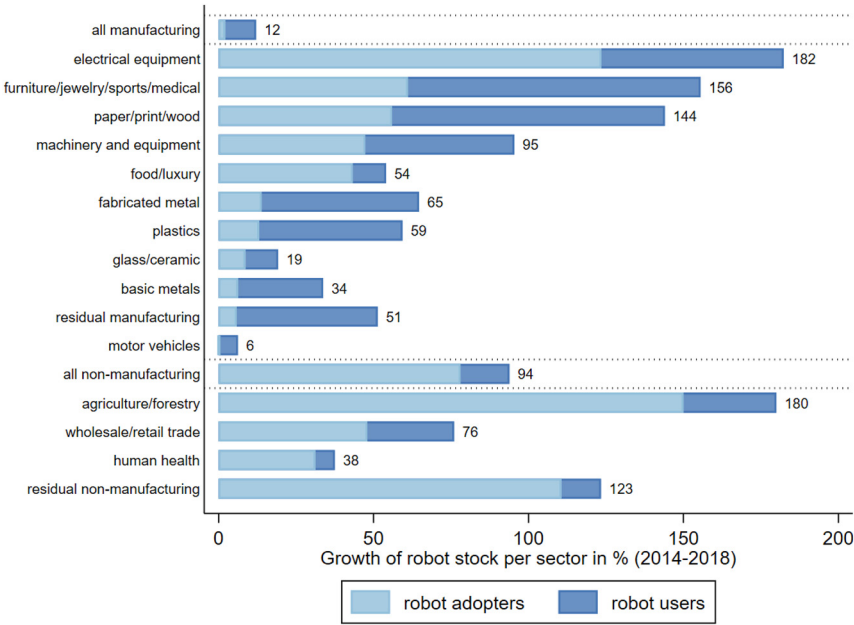


**Figure A2:** Share of robot users: 2014 versus 2018 (without survey weights). *Notes:* (1) No survey weights are applied. (2) A plant is identified as a robot user in 2018 if it answered yes to the question of whether it used robots from 2014 to 2018 and its robot stock in 2018 was not zero. (3) The 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 A3:** 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 A4:** Decomposition of growth in robot stock (without survey weights). *Notes:* 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.

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