Robots and Firms*

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Abstract

We study the microeconomic implications of robot adoption using a rich panel data-set of Spanish manufacturing firms over a 27-year period (1990-2016). We provide causal evidence on two central questions: (1) Which firm characteristics prompt firms to adopt robots? (2) What is the impact of robots on adopting firms relative to non-adopting firms? To address these questions, we look at our data through the lens of recent attempts in the literature to formalize the implications of robot technology. As for the first question, we establish robust evidence for positive selection, i.e., ex-ante better performing firms (measured through output and labor productivity) are more likely to adopt robots. On the other hand, conditional on size, ex-ante more skill-intensive firms are less likely to do so. As for the second question, we find that robot adoption generates substantial output gains in the vicinity of 20-25% within four years, reduces the labor cost share by 5-7%-points, and leads to net job creation at a rate of 10%. These results are robust to controlling for non-random selection into robot adoption through a difference-in-differences approach combined with a propensity score reweighting estimator. To further validate these results, we also offer structural estimates of total factor productivity (TFP) where robot technology enters the (endogenous) productivity process of firms. The results demonstrate a positive causal effect of robots on productivity, as well as a complementarity between robots and exporting in boosting productivity.

JEL codes: D22; F14; J24; O14;
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1 Introduction

The rise of robot technology has sparked an intense debate about the economic effects of robot adoption.[1] A key concern in this debate is that robots "steal" jobs from humans. A recent study by Acemoglu and Restrepo (2020) fuels this concern, finding large negative effects of robots on employment and wages across U.S. commuting zones. Other important economic variables like productivity growth, output prices, or even educational attainment are also affected by the rise of robot technology, as evidenced by Graetz and Michaels (2018) and Dauth et al. (2018). However, a considerable challenge in the entire literature so far is the lack of *micro-level* information on actual robot use. The few existing studies all resort to *macro-level* information by industry to construct measures of local or regional robot exposure. While this approach is useful in estimating the aggregate economic effects of robots, it makes the crucial assumption that all firms in a given industry have the same ability and willingness to adopt robots. It does not take seriously the possibility that some firms are considerably more likely to adopt robots (and thus positively or negatively selected); nor does it speak to the potentially important adjustments taking place within those firms, for example in terms of employment, wages and productivity. A *micro*-economic (firm-level) analysis is thus needed, in order to develop a more fine-grained and more far-reaching understanding of the economic implications of robot adoption (Raj and Seamans, 2018).

In this paper, we offer such an analysis. Our paper is the first attempt in the literature to investigate ex ante differences in robot adoption *across* firms, and estimate the microeconomic effects of robot adoption *within* firms.[2] To do so, we draw upon a unique panel data-set of Spanish manufacturing firms from the Encuesta Sobre Estrategias Empresariales (ESEE) over a 27-year period (1990-2016). A key novelty of our paper relative to existing studies is that our data-set includes explicit information on robot use in the production process of individual firms. Using this information in our analysis, we are able to sort out selection and treatment effects of robot adoption, by exploiting the longitudinal nature of our data-set and using state-of-the-art reduced-form as well as structural econometrics. This allows us to provide the first causal evidence on the following central questions: (i) Which firm characteristics raise the probability of firms to adopt robots? (ii) What is the (partial equilibrium) impact of robots on adopting firms relative to non-adopting firms?

Figure 1 constructed from the ESEE data-set provides a first indication that the adoption of robots is heterogeneous across firms. The left panel demonstrates that those firms that adopted robots between 1990 and 1998 ("robot adopters") *increased* the number of jobs by more than 50% between 1998 and 2016, while those firms that did not adopt robots ("non-adopters") *reduced* the number of jobs by more than 20% over the same period.[3] At the same time, the right panel indicates

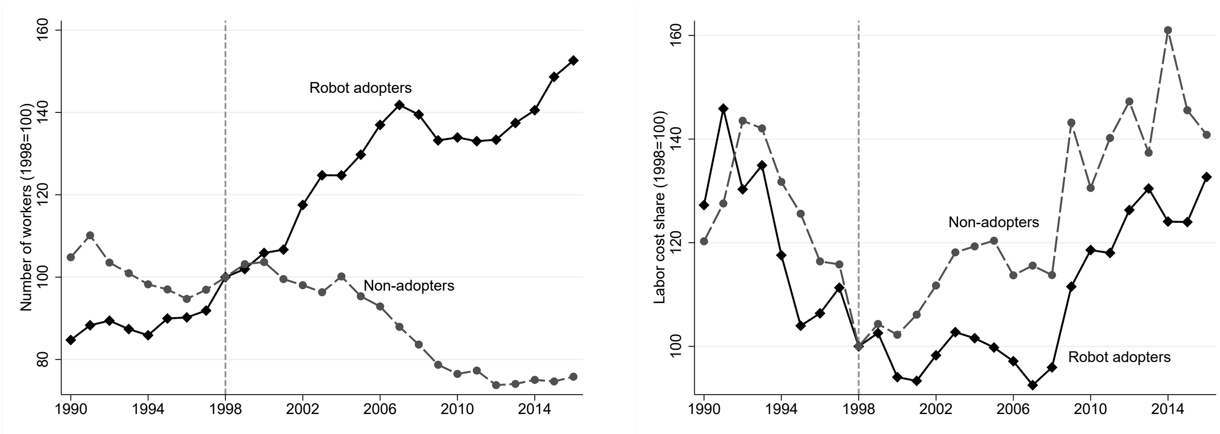
[1]Industrial robots differ from other technologies or capital equipment in that robots are automatically controlled and capable of doing different tasks (see UNCTAD, 2017, Ch.III p.38). In a broad sense, industrial robots are defined as "automatically controlled, reprogrammable, multipurpose manipulators, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (ISO 8373, for details see `https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en` accessed on Nov 20, 2020.)

[2]There is now an emerging literature using firm-level data to study the implications of modern technologies (automation or robots). We refer to this literature in greater detail below.

[3]To construct the figure, we balance the sample across the entire sample period from 1990 to 2016 and thus abstract

that robot adopters were able to reduce their labor cost shares relative to non-adopters between 1998 and 2016. From macro-level information on robot use, as employed in the existing literature, it is impossible to identify and investigate these striking patterns in the data.

Figure 1: Evolution of firm-level employment and labor cost share (1990-2016)



(a) Average firm employment

(b) Average firm labor cost share

Notes: The left and right panel depict, respectively, the evolution of average firm employment (measured by the number of workers) and the average firm labor cost share (defined as labor costs divided by the total production value), separately for robot adopters and non-adopters. The sample is balanced on firms from 1990-2016. Robot adopters are defined as firms that entered the sample in 1990 and had adopted robots by 1998. Non-adopters are firms that never use robots over the whole sample period.
Source: Authors' computations based on ESEE data.

To provide a suitable lens through which to interpret our data, we begin our analysis by developing a theoretical framework of firm-level robot adoption. Following Acemoglu and Restrepo (2018*a*), we combine a monopolistic competition framework with a task-based approach in which robots and labor are perfect substitutes for one another in a specific set of low complexity tasks ("automatable tasks").[4] To study across-firm differences in the incentives to adopt robots, we augment the model to allow for firm heterogeneity in terms of productivity, as in Melitz (2003). In its basic form, our model generates two connected and fundamental insights. First, robot adoption is characterized by positive selection. This means that firms with higher productivities are more likely to adopt robots. Secondly, since robots are productivity-enhancing, they raise firm-level output and market shares of robot adopting firms, and magnify productivity differences between adopters and non-adopters. While this opens up the possibility for net job creation in high-productivity robot adopting firms, it also implies that the least productive non-adopters are forced to exit the market, and that surviving

from entry into, and exit from, the sample. Moreover, we only keep those firms in the sample that did not use robots in 1990, and had either started to use robots by 1998, or never used robots throughout the sample period. The thus constructed sample consists of almost 100 firms with 675 and 1701 firm-year observations for the group of robot adopters and the group of non-adopters, respectively.

[4]There is a striking similarity between modeling automation and offshoring. In the offshoring literature, foreign labor is assumed to be a perfect substitute for domestic labor in offshorable tasks (e.g. Grossman and Rossi-Hansberg, 2008; Egger et al., 2015). This is also true for Groizard et al. (2014), who consider, as we do, the case of a CES production technology. Offshoring thus "parallels [the] analysis of machines replacing tasks" (see Acemoglu and Autor, 2011, p.69).

non-adopters lose market shares and reduce employment. These insights suggest the existence of two sources of aggregate productivity gains due to robot technology: (1) direct efficiency gains in those firms that adopt robots; and (2) indirect gains through labor reallocation that benefits those workers employed in robot adopting firms, while hurting those in non-adopting firms.

In our empirical analysis, we provide evidence broadly in line with this mechanism. We first focus on the adoption decision and identify which firm characteristics have a causal impact on the likelihood of robot adoption. We reveal strong evidence for positive selection, i.e., firms that adopt robots in their production process perform better (in terms of total output and labor productivity) than non-adopters already before adopting robots. We also establish evidence that, conditional on size, more skill-intensive firms are *less* likely to adopt robots. This finding is consistent with a version of our model featuring two skill types of labor as well as firm heterogeneity in the complexity of the production process. Intuitively, a more complex production process requires a larger share of high-skilled workers; since these workers are more difficult to replace, there is a negative relationship between the skill intensity of the firm and the gains from automation (see also Autor et al., 2003).[5] Finally, our data show that exporters are *more* likely to adopt robots than non-exporters, and we provide some evidence that this might reflect internal scale economies that can be harvested by serving foreign markets in addition to the domestic market, motivated from our theoretical framework.

We then proceed by investigating the output and labor market effects within robot adopting firms. Since the adoption decision is not random, but instead governed by, among other things, the firm's size and skill intensity, this analysis faces a fundamental endogeneity problem. To tackle this problem and credibly control for non-random selection into robot adoption, we closely follow the methodology proposed by Guadalupe et al. (2012) and combine a difference-in-differences approach with a suitable propensity score reweighting estimator. This allows us to establish the following results. First, we find positive and significant output effects of robot adoption. Our estimates imply that the adoption of robots in the production process raises output by almost 25% within four years. Secondly, we find that robots raise firm-level employment by around 10 percent. Importantly, we find strictly non-negative employment effects across the board for all types of workers, including low-skilled workers as well as workers employed in the firm's manufacturing establishments. Finally, we estimate a significant decline in the labor cost share by almost 7 percentage points following robot adoption. These results are consistent with our theoretical framework, where robot adopters reduce their labor cost shares, while the impact on employment is ambiguous and depends on the relative strength of the displacement effect and the productivity effect of robot adoption.

We also investigate how non-adopting firms, i.e., firms that do not start using robots, are affected by the rise of robot technology. We reveal significant job losses there. When robot firms generate half of total industry sales, 10% of jobs in non-adopting firms are lost (relative to a counterfactual without robots). The same logic applies to changes in output, but the implied magnitude is even more pronounced. Looking at survival probabilities, we document significantly higher exit rates

[5] In a similar vein, we find evidence that firms with lower shares of manufacturing and production workers are less likely to adopt robots, too.

among non-adopters due to an increase in the industry's robot density, which is consistent with the predicted increase in the survival cut-off productivity in our theoretical framework. Importantly, our results are robust to using different measures of robot density, including the industry-specific stock of robots from the International Federation of Robotics (IFR).

In a final step of our empirical analysis, we draw upon a structural estimation framework, in order to estimate the causal effect of robot adoption on the firm's total factor productivity (TFP). To do so, we exploit estimation techniques similar to those proposed in De Loecker (2013) and Doraszelski and Jaumandreu (2013), who allow for endogenous productivity processes and investigate the relationship between firm-level productivity and exporting or R&D activities, respectively, and account for the self-selection of larger firms into these firm-level activities. The main identification assumption in our set-up is that firms cannot immediately adjust their production process and adopt robots in case they are hit by a positive demand or productivity shock. Our results indicate small but positive effects of robots on TFP. Remarkably, our estimates reveal that the productivity gains from robot adoption only accrue within those firms that are also exporters. As exporters serve larger markets than non-exporting firms, this is evidence that the scale of operations is a critical channel through which exporting supports productivity-enhancing innovations within firms.[6] We then use our TFP estimates to compute the productivity evolution in the Spanish manufacturing sector at large. García-Santana et al. (2020) have shown that TFP in Spain fell between 1995 and 2007, despite the fact that this was also the longest period in Spain with uninterrupted economic growth. While our estimates confirm this pattern for our sample, we also document that most of the decline in productivity in Spanish manufacturing in our sample can be attributed to non-adopters.[7]

Our paper contributes to a recent literature that investigates the labor market implications of robot technology. The influential paper by Frey and Osborne (2017) was one of the first to examine how susceptible jobs are to computerization. They argue that almost 47% of total U.S. employment can be automated in the nearest future. In their paper, computerization is defined as job automation by means of computer-controlled equipment. Three recent contributions focus specifically on robot adoption by using variation across countries and industries employing data from the IFR. Focusing on the period from 1993 to 2007 and covering 17 different countries, Graetz and Michaels (2018) find that the growing intensity of robot use accounted for 15% of aggregate economy-wide productivity growth, contributed to significant growth in wages, and had virtually no aggregate employment effects. Acemoglu and Restrepo (2020) and Dauth et al. (2018) use a local labor market approach to estimate the effects of robots on employment, wages, and the composition of jobs. Focusing on the U.S. between 1990 and 2007, Acemoglu and Restrepo (2020) find that one more robot per thousand workers reduces the employment to population ratio by about 0.2 percentage points and wages by 0.37 percent within commuting zones. Looking at Germany between 1994 and 2014, Dauth

[6] These findings are consistent with Lileeva and Trefler (2010), Aw et al. (2011), and De Loecker (2013). For example, in Aw et al. (2011), firms can endogenously decide to invest in R&D and start exporting. In their sample, plants in the Taiwanese electronics industry prove to have stronger incentives to select into both activities rather than just one of them.

[7] These findings speak to the misallocation of resources across high- and low-productivity firms to explain the TFP evolution in Southern Europe (see Gopinath et al., 2017, among others).

et al. (2018) find no effects on total employment, but identify a substantial shift in the composition of jobs, away from manufacturing jobs and towards business service jobs. Moreover, they show how the use of robots increases local labor productivity, but depresses the labor share in total income.

While these studies provide important and novel evidence on robot adoption, using statistics at the industry level precludes an in-depth analysis within and between firms. In our study, we document selection based on observable firm characteristics (size, labor productivity, worker characteristics, and exporting) and reveal positive employment and output effects in those firms that start to use robots, while negative employment (and output) effects arise from lower market shares for non-adopting firms. Furthermore, we demonstrate that the productivity gains documented in Graetz and Michaels (2018) or Dauth et al. (2018) might be partly explained by a reallocation of workers from low-productivity non-adopting firms to high-productivity robot adopters. In other words, with selection of more productive firms into robot adoption, increased exposure to robots reduces market shares of non-adopters and forces the least productive firms to exit. This across-firm reallocation affects aggregate industry productivity and speaks to "enormous and persistent measured productivity differences across producers, even within narrowly defined industries" (Syverson, 2011, p.326). Taking stock, by using detailed firm-level panel data from Spain for an extensive period of time, our paper allows to fill an important gap in recent attempts to investigate how automation affects productivity and labor markets.

Our study is part of a newly emerging literature studying the economic implications of modern technologies (automation or robots) based on firm-level data. The findings in Acemoglu et al. (2020) confirm to a large extent results presented in this paper. They find that robot-adopting firms in France reduce the labor share and the share of production workers while experiencing increases in value added and productivity. Moreover, the increase in overall employment in robot-adopting firms comes at the expense of their competitors. Humlum (2019) uses administrative data from Denmark, linking workers, firms, and robots, to investigate the distributional impact of robots across occupations. He finds that robot adopters expand output and substitute production workers with tech workers – such as engineers, researchers, and skilled technicians – and that robots are responsible for a quarter of the fall in the employment share of production workers since 1990. While we also detect positive output effects for robot adopters, we do not find such differential effects of robot adoption across occupations. Bessen et al. (2020) and Kromann and Sørensen (2020) investigate the implications of automation beyond robotics, by linking firm-level survey data on automation with other worker and firm characteristics in the Netherlands and Denmark, respectively.

The remainder of our paper is organized as follows. In Section 2, we describe the ESEE data-set and provide first descriptive evidence on the use of robots across firms, industries, and time. In Section 3, we provide a theoretical perspective on firm-level robot adoption that guides us in our subsequent empirical analysis. In Section 4, we analyze the robot adoption decision of firms, and in Section 5 we investigate the firm-level effects of robot adoption, especially output and labor market effects. In Section 6 we offer results from a structural framework to estimate firm-level TFP allowing robots to impact the (endogenous) productivity process of firms. Section 7 concludes.

2 Data

Our empirical analysis is based on data collected by the Encuesta Sobre Estrategias Empresariales (ESEE) and supplied by the SEPI foundation in Madrid. The ESEE is an annual survey covering around 1,900 Spanish manufacturing firms each year with rich and very detailed information about firms' manufacturing processes, costs and prices, technological activities, employment, and so forth. For the purposes of our research, the key aspect that sets the ESEE data-set apart from other data-sets is that it contains firm-level information on the use of robots in production. Hence, it provides a unique opportunity for studying the incentives for, as well as the consequences of, robot adoption at the firm level. In the following, we provide details on the specific data we exploit in our analysis and we document novel facts, drawn from out data, about robot diffusion and robot adoption in Spanish manufacturing.

Our study exploits data across 27 years spanning the years from 1990 to 2016. This is the complete sample period currently available from the ESEE. It provides a unique opportunity to investigate the drivers and consequences of profound changes in robot diffusion over roughly the last three decades. The initial sampling of the data in 1990 had a two-tier structure, combining exhaustive sampling of firms with more than 200 employees and stratified sampling of firms with 10-200 employees. In the years after 1990, special efforts have been devoted to minimizing the incidences of panel exit as well as to including new firms through refreshment samples aimed at preserving a high degree of representativeness for the manufacturing sector at large.[8] In total, our data-set represents an unbalanced sample of some 5,500 different firms. In the data, we can distinguish between 20 different industries at the 2-digit level of the NACE Rev. 2 classification and six different size groups defined by the average number of workers employed during the year (10-20; 21-50; 51-100; 101-200; 201-500; >500); combinations of industries and size groups serve as stratas in the stratification. We express all value variables in constant 2006 prices using firm-level price indices derived from the survey data or, where necessary, industry-level price indices derived from the Spanish Instituto Nacional de Estadistica (INE).

Most importantly for our analysis, we exploit information on whether a firm uses robots in the production process. The survey asks firms: *"State whether the production process uses any of the following systems: 1. Computer-digital machine tools; 2. Robotics; 3. Computer-assisted design; 4. Combination of some of the above systems through a central computer (CAM, flexible manufacturing systems, etc.); 5. Local Area Network (LAN) in manufacturing activity"*.[9] Based on this question,

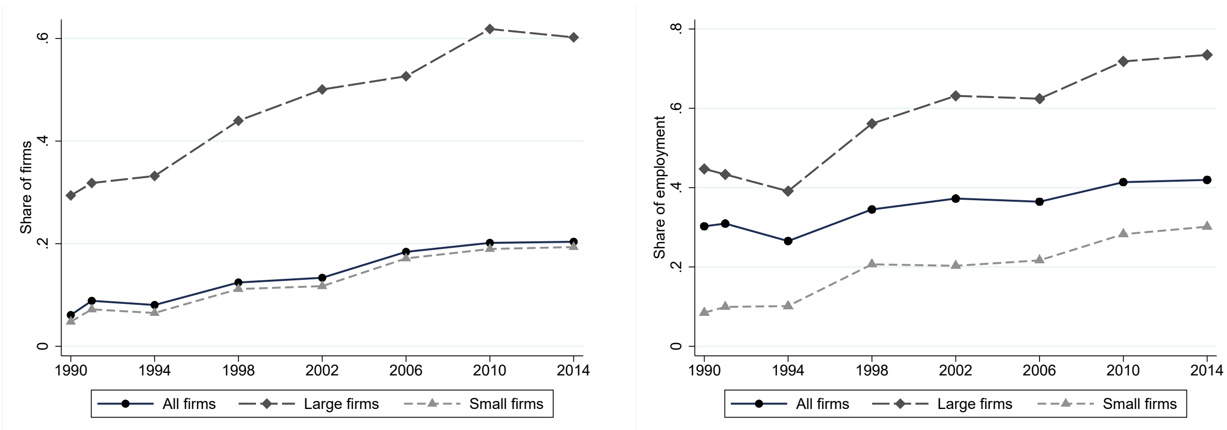
[8] For details see `https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp` (accessed on Nov 20, 2020).

[9] The original questionnaire is distributed in Spanish. The question in Spanish is: *"Indique si el proceso productivo utiliza cada uno de los siguientes sistemas: 1. Máquinas herramientas de control numérico por ordenador; 2. Robótica; 3. Diseño asistido por ordenador (CAD); 4. Combinación de algunos de los sistemas anteriores mediante ordenador central (CAM; sistemas flexibles de fabricación, etc.); 5. Red de Área Local (LAN) en actividaded de fabricación"*. In 1990, the possible answers were slightly different: *"1. CAD/CAM; 2. Robótica; 3. Sistemas flexibles de fabricación; 4. Máquinas herramientas de control numérico"*.

we construct a 0/1 robot indicator variable equal to one if the firm uses robots and zero otherwise. We also use information on the other systems and generate indicators for CAM, CAD, and FLEX, respectively (more on this below).[10] The robot information is available every four years, starting in 1990. In addition, firms report the use of robots in the year 1991, as well as in the first year they enter the sample.[11] Before describing other variables we use in our empirical analysis, we document some patterns of robot use across time and industries by using the full sample of firms available in the data.

2.1 A first look across industries

Figure 2: Evolution of robot diffusion in Spain (1990-2014)



(a) Share of firms using robots (b) Employment shares corresponding to robot firms

Notes: The left panel depicts the share of firms using robots in their production process. The right panel depicts the share of total employment in firms using robots. The solid black lines consider all firms in the sample, while the dashed gray lines consider, respectively, large firms (those with more than 200 employees) and small firms (those with up to 200 employees). Both figures are based on the full sample of firms.

Figure 2 depicts the evolution of robot diffusion in the Spanish manufacturing sector over the period 1990-2014. The left panel shows that, among all firms, just about 6% were using robots in 1990. This share has grown considerably over time, to more than 20% in 2014. The figure also reveals very significant differences in robot use between small firms (those with up to 200 employees) and large firms (those with more than 200 employees). For example, in 1990 already around one third of large firms had adopted robots, while the same number for small firms was less then 5%. The difference between these shares has grown over time, such that in 2014 about 60% among large firms use robots vs. almost 20% among small firms. The right panel of the figure shows the evolution of employment shares corresponding to robot firms. In 2014, more than 40% of all

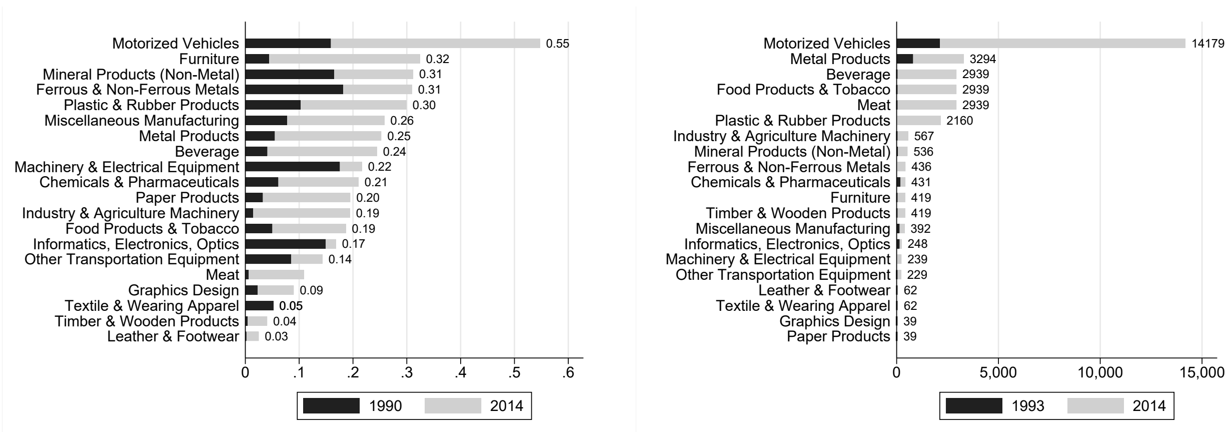
[10]CAM, CAD, and FLEX are 0/1 indicator variables equal to one if the firm uses, respectively, computer-digital machine tools (CAM), computer-assisted design (CAD), and a combination of systems through a central computer (FLEX). We do not use information on Local Area Network adoption since it is only available from 2002 onwards.

[11]This means that we have robot information available in 1990, 1991, 1994, 1998, 2002, 2006, 2010, and 2014 for all firms included in the sample in the respective years. Moreover, we have robot information available in the remaining years (i.e., 1992, 1993, 1995,...) for those firms that appear in the sample for the first time in the respective years.

workers were employed in firms using robots, while the same number was more than 70% (35%) when only considering employment in large (small) firms. Taking stock, robot firms represent a highly significant part of modern Spanish manufacturing, especially among large businesses.[12]

Our data also reveal a high degree of heterogeneity in robot diffusion and robot adoption rates across industries. The left panel of Figure 3 depicts the share of firms in our ESEE data-set using robots for 20 different industries, separately for the years 1990 and 2014. In 1990, the top-3 robot-using industries were Ferrous & Non-Ferrous Metals (18%), Machinery & Electrical Equipment (18%), and Motorized Vehicles (16%). By 2014, this ranking had changed and the top-3 industries were then Motorized Vehicles (55%), Furniture (32%), and Mineral Products (Non-Metal) (31%). Thus, we see huge cross-industry differences in the share of firms using robots at a given point in time, as well as in the adoption rates between 1990 and 2014. Robot adoption at the industry level occurs with varying pace and magnitude.

Figure 3: Robot diffusion across industries: Comparison of Data Sources



(a) ESEE data (b) IFR data

Notes: The left panel shows the share of robot firms by industry using the full sample of firms available in the ESEE data. The right panel shows the stock of robots using the IFR data set. Black bars show data for 1990 (1993) in the left (right) panel and gray bars for 2014.

The patterns presented in our ESEE data-set are consistent with alternative data on robots in Spanish manufacturing industries. Existing papers investigating the impact of robot diffusion rely mainly on industry statistics offered by the International Federation of Robotics (IFR) (e.g. Acemoglu and Restrepo, 2020; Dauth et al., 2018; Graetz and Michaels, 2018). In the right panel of Figure 3 we use data from the IFR and plot the industry-specific stock of robots separately for the years 1993 (the first year where data on the stock of robots is available in the IFR data) and 2014.[13] Comparing the left and right panel of Figure 3 indicates qualitatively similar results for

[12]Spanish manufacturing is a particularly interesting case to look into due to high robot density relative to other countries. For instance, Spain had 160 robots per 10,000 employees in 2016, while the world average was 74 robots according to the International Federation of Robotics. In the same year, Spain was the country with the fourth-largest operational stock of robots in Europe (behind Germany, Italy and France). Spain was also among the fastest robot adopters in the 1990s and 2000s, with annual growth rates for the operational stock of robots around 20-30%.

[13]Table A.1 in online Appendix A.1 describes the concordance between the different industry classifications in the

the ranking of industries. For example, motorized vehicles, metal products and plastic & rubber products are listed among the leading industries in 2014 in both data-sets, while graphics design, textile & wearing apparel and leather & footwear turn out to be industries with the lowest robot diffusion. Furthermore, Figure A.1 in the online Appendix compares how robot diffusion has evolved according to both data-sets. Comparing how the share of robot firms in the ESEE data has evolved relative to the market value or the stock of robots (both available in the IFR data), again reveals a high degree of similarity.

2.2 Turning towards a firm-level perspective

We now continue by describing in more detail our data-set and the variables we employ in our empirical analysis. Throughout the next sections we focus on firm characteristics explaining the adoption of robots and the respective treatment effects. Hence, our focus is on firms switching from non-robot use to first-time robot use and we therefore restrict our sample to firms that do not use robots in the first year they appear in our data in sections 4 and 5. Moreover, we drop sample observations after a firm undergoes a major restructuring due to changes in corporate structure (e.g. following a merger with another firm). This allows us to eliminate from the analysis situations connected with huge employment or output changes that are unrelated to robot adoption. In total, we have 4,446 different firms in the thus restricted sample. 644 (15%) of these firms adopt robots at some point in time within our sample period ("robot adopters") and 3,802 (85%) never adopt robots ("non-adopters"). Furthermore, 397 firms (62%) among robot adopters keep on using robots throughout, while 177 (27%) report the use of robots for a certain period of time and abandon them afterwards.[14] 70 firms (around 10% of robot adopters) switch back and forth several times.[15] For our purposes, it is unclear how to interpret these multiple switches and we therefore drop this last group of 70 firms from our analysis on the selection and treatment effects in sections 4 and 5.[16] In Table A.2 in the online Appendix we report how the 644 cases of robot adoption are distributed across time and industries. Not surprisingly, the total number of robot adopters is the highest in those industries that also turn out to be the industries with the highest density of robot adopters (see Figure 3). However, robot adoption turns out to be evenly distributed across time for all industries and is not concentrated in the most recent years of our sample.

In the next step we provide insights whether the switch into robot adoption is associated with

ESEE and the IFR data-sets.

[14]We have also investigated whether firms that stop using robots are different from firms that use robots continuously, and which factors could explain the decision to stop using robots. First, we do not find any significant differences among the two groups of firms. Secondly, it turns out that only the firm's output predicts the likelihood to stop using robots to some extent, in the sense that smaller firms are more likely to stop using robots. Details on this can be found in online Appendix A.8 to this paper.

[15]Specifically, 54 firms report the use of robots for two distinct periods of time (meaning that they do not use robots in between), while 16 firms start using robots (and abandon them) several times.

[16]We have verified that our results are robust to using different samples. In the online Appendix we present estimation results akin to those presented throughout sections 4 and 5, but derived from two different samples. The first sample includes all 644 firms that start using robots, even though some of them switch back and forth several times. The second sample restricts the focus to those 397 firms that start to use robots and continuously report to use robots in the production process afterwards.

other variables, specifically investment and innovation activities carried out by those firms. To do so, we conduct an event study analysis which attempts an exploration of the timing of investment and innovation associated with the adoption of robots.[17] For each robot adopter we define an integer variable I measuring the difference between the current year t and the year of robot adoption. For example, for a firm adopting robots in the year 2002, the variable is equal to -2 in 2000, -1 in 2001, 0 in 2002, +1 in 2003, +2 in 2004, and so on. To conduct a simple before-after analysis we restrict the sample to the 644 robot adopting firms and estimate the following equation:

$$y_{it} = \sum_{k=-4}^{4} \gamma_k \mathbb{1}(I = k)_{it} + \mu_i + \mu_{st} + \epsilon_{it}, \tag{1}$$

where y_{it} denotes the dependent variable, the indicator variable $\mathbb{1}(I = k)_{it}$ is equal to one if $I = k$ for firm i in year t (and zero otherwise), μ_i and μ_{st} denote firm and industry-year fixed effects, respectively, and ϵ_{it} is the error term.[18] For the dependent variable we distinguish between four different outcomes: (*i*) the value of the firm's capital stock (in logs), (*ii*) investments in machinery (in percentages of purchases of tangible fixed assets), (*iii*) the stock of process innovations in computer programs attached to manufacturing processes, and (*iv*) the stock of innovations in terms of organizational methods (external relationships or workforce organization).[19] The choice of the dependent variables is motivated by the fact that one might expect hikes in capital, or even more specifically, in investments in machinery, in the years just before the adoption of robots. Furthermore, the decision to adopt robots might also be associated with other types of innovation activities before and after the adoption, and we therefore choose two indicators that have been used in previous studies on innovation using the ESEE data-set.[20]

We then plot the γ_k coefficients against the values of I to obtain a fine-grained picture of the changes in investment and innovations before and after the adoption of robots.[21] From inspection of the upper panels in Figure 4 we see that firms indeed have a hike in investment activities, as the reported γ_k coefficients turn out to be positive and significant differently from zero before, but not after, the adoption or robots. Looking at the lower panels, we see that the adoption of robots is also associated with other types of process innovations, and intuitively, innovations in labor reorganization after the adoption of robots.

[17] Our event study analysis largely follows Balasubramanian and Sivadasan (2011).

[18] Given the time period available in our analysis (1990-2016), we have a small number of observations for relatively large positive and relatively large negative values of I. We restrict the focus to four years before and four years after the adoption of robots, as the robot information is available every four years in our data-set. We have verified that the results are robust to winsorizing I at e.g. -5 on the lower end and at $+5$ at the upper end.

[19] The two innovation variables are based on dummy variables indicating whether the firm carried out the respective activity in a given year.

[20] For instance, Guadalupe et al. (2012) use the ESEE data-set and investigate how changes in ownership from domestic to foreign affect the innovation activities of acquired firms. To do so, they employ different measures of innovation, including the two innovation measures we employ here. Specifically, they focus on the stock of innovations since the firm entered the sample, since "at any point in time, the firm's technology can be characterized as the sum of innovations made up to that point" (cf. Guadalupe et al., 2012, p.3610).

[21] Note that the inclusion of firm and industry-year fixed effects "controls for age-to-survivor bias by controlling for industry-specific age trends" (cf. Balasubramanian and Sivadasan, 2011, p.136).

Our analysis is based on a robot adaption variable that relies on a very generic yes or no question in the survey. This might raise concerns regarding the usefulness of our measure for adoption. To address such concerns and to verify that the variable carries significant informational content, we conduct a placebo event study analysis. We first classify specific firms among the group of non-adopters as *placebo* adopters. To do so, we exploit the propensity scores estimated for the treatment analysis in Section 5, with the aim of replicating the frequency and other firm characteristics of *actual* adopters.[22] Using the estimated propensity scores, we generate a sample with placebo-treated firms; for each placebo-treated firm, we define the year in which the estimated propensity score is largest as the adoption year. We assign the top 5% of non-adopters that are most likely to adopt robots into the group of robot adopters.[23] We then repeat the event study analysis for the constructed sample of placebo robot adopters. Finding (placebo) effects would cast doubt on our findings and the variable measuring robot adoption. However, our event study reveals no placebo effects, whether we look at the firm's capital stock, investments in machinery, the stock of process innovations, or the stock of innovations in terms of organizational methods. Within the constructed sample, the reported γ_k coefficients are not statistically different from zero (see Figure A.2 in the online Appendix), indicating no hike in investment or innovation activities around the placebo treatment.

Lastly, Table A.3 in the online Appendix presents descriptive statistics on the various variables we employ in our empirical analysis throughout sections 4 and 5. We pool the data across all years and then sort observations into groups of firms that adopt robots at some point in time and those that never use robots within our sample period. The table reveals some suggestive differences between the two types of firms. Robot adopters turn out to be superior firms in many dimensions. They produce more output, they are more productive, and they employ more workers, even when focusing on just workers in manufacturing jobs or just low-skilled workers.[24] Moreover, while robot adopters pay a higher average wage, they have a lower average labor cost share than non-adopters. In addition, robot adopters are more "globalized", in the sense that they are more likely to export, import, be in foreign rather than domestic ownership, and assimilate foreign technologies.[25] Of course, these differences may be caused by factors unrelated to the adoption of robots. In the empirical analysis that follows later on, we will try to sort out which of the differences between

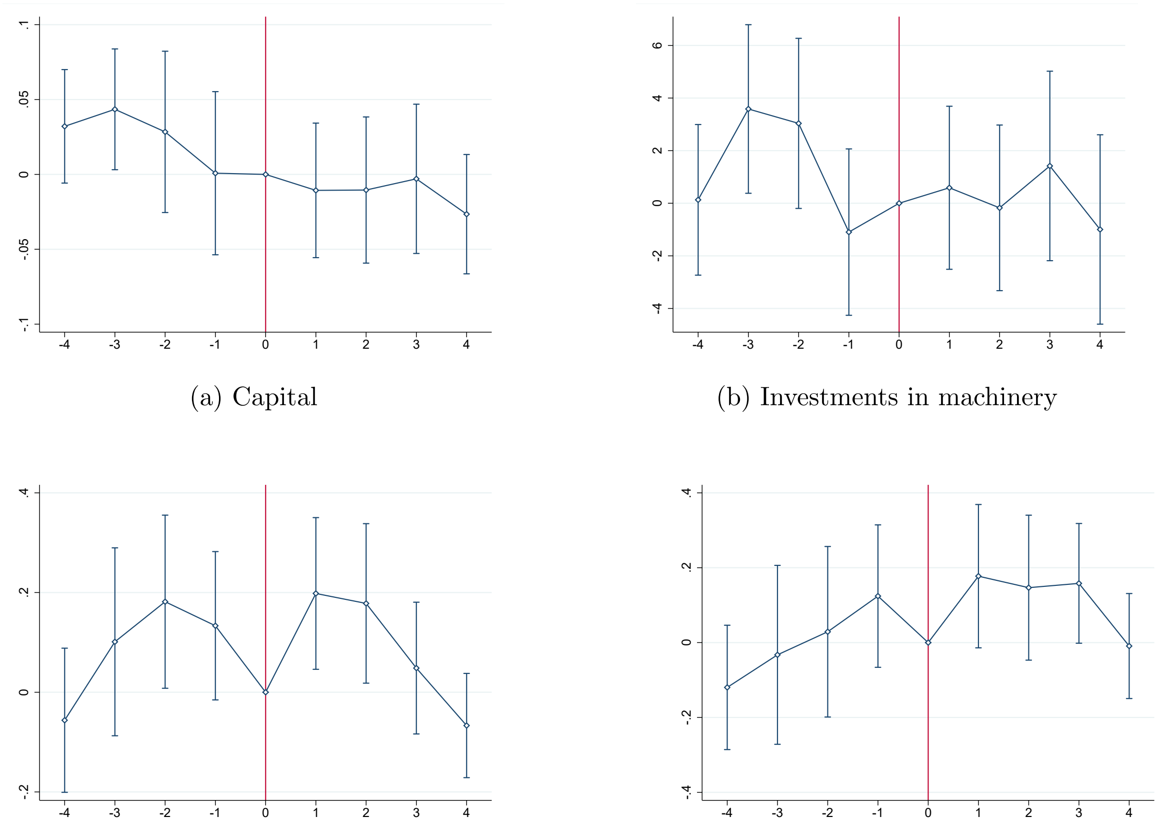
[22]There, we obtain propensity scores for all firms by running industry-specific probit regressions for robot adoption (the treatment) on one-year lags of sales, sales growth, labor productivity, labor productivity growth, capital-, skill- and R&D-intensity, indicators for exporter, importer and foreign ownership, and year dummies.

[23]This gives us a sample of 123 firms (1,197 firm-year observations) that are classified as placebo robot adopters. Like actual adoptions, placebo adoptions span across virtually all years and are distributed across all industries, as in Table A.2 in the online Appendix. We also constructed different samples for which the results are very similar. As one alternative, we assign the top 10% of non-adopters that are most likely to adopt robots into the group of robot adopters. As yet another alternative, we made use of different propensity scores.

[24]As in Guadalupe et al. (2012), we measure labor productivity as value added per worker, where value added is defined as the sum of sales plus change in inventory, less purchases and costs of goods sold.

[25]This finding speaks to studies investigating technology upgrading in the global economy. For example, Bustos (2011) provides evidence that exporters intensify their investments in technology after a trade liberalization process, while Lileeva and Trefler (2010) document how improved foreign market access prompted plants in Canada to adopt more advanced technologies.

Figure 4: Event study analysis: Before-after effects



(a) Capital

(b) Investments in machinery

(c) Process innovations

(d) Innovations in terms of organizational methods

Notes: Points on the graph are the $\gamma_k, k \in -4, ..., 4$, coefficients in the estimating equation 1. The values of the dependent variable are normalized to zero in the year the firm adopts robots, so that $\gamma_0 = 0$. The underlying sample consists of 644 firms that adopt robots over the sample period. Vertical lines represent 90% confidence intervals.

robot adopters and non-adopters already existed before firms started to adopt robots, and which are causally associated with robot adoption.[26]

3 A theoretical perspective on firm-level robot adoption

This section provides a theoretical framework for our empirical analysis on selection into robot adoption and its treatment effects in the subsequent sections 4 and 5. It draws from recent attempts in the literature to formalize the implications of robot technology, and serves to reveal the main economic trade-offs that we can expect to be at play at the firm level. We use our theoretical framework to derive hypotheses about the decision of firms to adopt robots, as well as about the implications of robot adoption for output, labor costs and labor demand. In the interest of space

[26]Table A.4 in the online Appendix provides summary statistics for the full sample that we use in section 6, including those firms that use robots already in the first year they appear in the sample. We have also looked at these firms separately. Not surprisingly, these firms turn out to be special. As for the group of robot adopters, these firms turn out to be superior firms in many dimensions. They produce more output, they are more productive, and they employ more workers.

and readability, we confine ourselves to an intuitive discussion in the main text. We support this discussion with detailed analytical derivations in online Appendix A.6.

3.1 Basic set-up

Consider an industry in which a large number of monopolistically competitive firms (indexed by ω) produce horizontally differentiated goods facing an iso-elastic demand. As for production, we follow Acemoglu and Restrepo (2018*b*) in writing output as a composite of different tasks combined in a constant elasticity of substitution aggregate. However, we depart from Acemoglu and Restrepo (2018*b*) by introducing two types of firm heterogeneity into their framework. Specifically, we allow firms to differ (i) in terms of their productivity (and thus size), as in Melitz (2003), and (ii) in the complexity of their tasks (and thus the likelihood of tasks being automated). We index tasks by i and assume that they can be ordered according to their complexity where a higher index i reflects higher complexity. The parameter $N(\omega)$ governs the set of tasks the firm has to perform. The two production factors, robots and labor, are perfect substitutes for one another in all tasks, which highlights an important aspect of automation, namely that machines are used to substitute for human labor (Acemoglu and Restrepo, 2018*a*, p.2). We assume that, while human labor has a comparative advantage in performing more complex tasks than robot capital, effective robot capital costs for all technologically automatable tasks are strictly below the effective labor costs. Firms endogenously decide upon the range of tasks performed by robots, but any degree of automation requires the payment of a fixed cost.

3.2 The robot adoption decision

In a first step, we use our theoretical model to derive predictions on the decision of firms to adopt robots, which we can confront with our Spanish firm-level data.

3.2.1 Productivity

Firms face a standard trade-off when deciding upon automation. The reduction in variable costs requires the payment of a fixed cost. Thereby, the profit gain from robot adoption is increasing in a firm's baseline productivity, as ex-ante larger and more productive firms serve a larger market and have a higher incentive to lower their variable production costs, i.e. they are more likely to adopt robots in production.

3.2.2 Exporting and imports of technology

Suppose firms can choose to serve consumers not only in the domestic but also in the foreign economy. While the foreign economy is fully symmetric to the domestic economy, exporting requires the payment of a fixed export cost and per-unit iceberg type transport costs, denoted by F^x and τ, respectively. As is well-known, the introduction of a fixed export cost generates (sharp) selection of ex-ante more productive firms into exporting. Hence, we end up with four different cutoffs leading to combinations of robot adopters vs. non-adopters and exporters vs. non-exporter. Table A.5 in the online Appendix reveals that, in our data, the share of exporting firms exceeds the share of robot adopting firms across all industries. We therefore focus on cost and parameter conditions that guarantee that the least productive firms serve only the domestic market and do not adopt robots, while more productive firms export and only the most productive exporters find it attractive to adopt robots. Due to symmetry of the two countries, operating profits of exporting firms are now scaled by a constant factor $1 + \tau^{-\beta/(1-\beta)}$, where β controls the constant elasticity of substitution $1/(1-\beta) > 1$ between any two varieties. This is similar to Bustos (2011), and we can conclude that exporters have stronger incentives to adopt robots as the gains from doing so—the reduction in variable production costs—can be scaled up to a larger customer base in home *and* foreign.[27]

Clearly, in an open economy one could think about alternative explanations, different to the scale effect, why exporters are more likely to adopt robots. One alternative are knowledge spillovers in an open economy, giving firms easier access to foreign technologies (robots). Such spillovers could arise among all firms or they could be firm-type specific, for example such that a reduction in the fixed cost of robot adoption arises only among the group of exporting firms. Yet, another alternative, is that trade liberalization intensifies competition and therefore increases the pressure of productivity enhancing investments, a mechanism that finds recent support in Autor et al. (2020). In the empirical analysis below, we further investigate these alternative mechanism using specific firm-level information available in our data-set, e.g. information on the assimilation of foreign technologies.

3.2.3 Complexity of the production process

Since human labor has a comparative advantage in more complex tasks, cost savings from robot adoption are lower for firms featuring a more complex production process. Unfortunately, in the ESEE data-set we do not observe tasks or occupations to compute firm-specific measures of task complexity, e.g. measures for routinness of production as in the offshoring literature (e.g. Levy and Murnane, 2004; Blinder, 2006). However, we can proxy task complexity by the skill composition of firms in our empirical analysis. To rationalize this approach, suppose there are two types of human labor, low-skilled and high-skilled workers, referenced by subscripts l and h, respectively, and corresponding wages w_l and w_h. Following Acemoglu and Autor (2011), we assume that high-skilled workers have a comparative advantage over their low-skilled coworkers in the performance of more complex tasks. Specifically, we assume that the relative efficiency of high- to low-skilled labor, $\gamma_h(i)/\gamma_l(i)$, is strictly increasing in i. In such an environment, firms will not only compare the production costs of robots and human labor across tasks, but also consider the skill-specific effective labor costs in each task, i.e., the firm will benchmark $w_l/\gamma_l(i)$ against $w_h/\gamma_h(i)$. Given

[27] Alternatively, we could set costs and parameters such that only the adoption of robots makes firms sufficiently productive to serve both foreign and domestic customers. Put differently, by ranking firms such that only the most productive robot adopters find it attractive to start exporting, an improvement in robot technology raises the probability of exporting. While we do not find any positive and significant impact of robot adoption on exporting (or the share of export sales), we reveal a complementarity between exporting and robot adoption in Section 6.

that high-skilled workers have a relative advantage in performing more complex tasks, this results in a cut-off task at which firms are exactly indifferent between hiring high-skilled and low-skilled workers for the performance of that task. Comparing two otherwise identical firms that differ only in the complexity of their production process, we find that the firm with higher $N(\omega)$ employs a higher share of high-skilled workers. Since firms with higher $N(\omega)$ are less likely to adopt robots, we have established a negative link between the skill intensity of firms and their propensity to adopt robots.[28]

3.3 The effects of robot adoption

Having discussed the decision of firms to adopt robots, we now focus attention to the *effects* of robot adoption, both at the firm and the industry level.

3.3.1 Firm-level effects

First of all, since robots have a comparative advantage in the production of automatable tasks, it is straightforward that robot adoption raises firm output. Moreover, due to our assumptions on the task production function in Eq. (A.3), it follows immediately that robot adoption reduces the labor cost share, as robots substitute human labor in automated tasks. The overall impact of automation on labor demand within firms is, however, ambiguous. It depends on two opposing effects: on the one hand, the *displacement effect* reduces demand for labor since part of the workforce is substituted by robots. On the other hand, the *productivity effect* entails that robots raise the efficiency in production, and thus output and employment. Similar to the offshoring literature (see Grossman and Rossi-Hansberg, 2008), the productivity gains may be strong enough to outweigh the losses, so that total firm-level employment increases. Clearly, the strength of the displacement effect depends on the share of automatable tasks, while the magnitude of the productivity effect depends on the variable cost savings from robot adoption. A final question is which skills (and thus workers) are specifically affected by automation. Using the model with two skill types of labor from above, it is clear that low-skilled workers are more likely to be affected by automation, since they perform the less complex tasks which are the ones being automated. However, as long as the low-skilled workers are not fully replaced by robots, the productivity effect is also working in their favor. This is the case as long as the level of robot technology is below the cut-off task at which firms are indifferent between employing high- and low-skilled labor.

3.3.2 Industry-level effects

We can use the model to study the industry-level effects of changes in the fixed cost of adopting robot, which are similar to changes in the level of robot technology that increase the share of automatable tasks. A decrease in fixed costs, decrease the cut-off productivity that separates robot

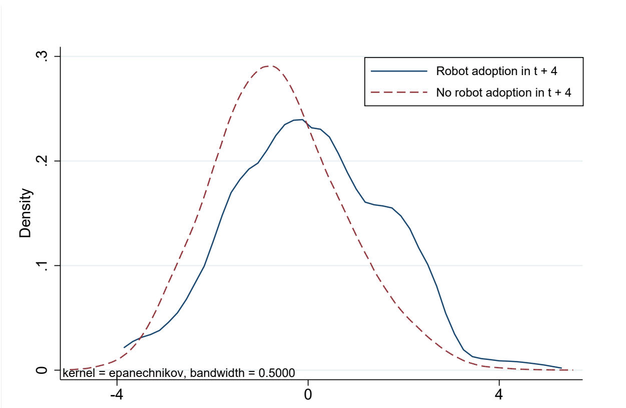
[28]We restrict the focus to two types of skill here, as we cannot distinguish between multiple skills (or occupations) in our data-set. However, in the online Appendix we discuss how the model can be extended to multiple skills. We also discuss there how one can allow for a skill bias in robot adoption.

adopters from non-adopters and thus raise industry-level robot exposure. Similar to Melitz (2003), this has important implications for the industry equilibrium. As ex-ante more productive firms gain market shares by reducing marginal costs due to robot adoption, it raises the cut-off productivity at which firms are able to survive in the market. Put differently, increasing robot exposure at the industry level prompts the least productive firms to exit, and the surviving non-robot firms to reduce their output and employment. This mechanism, along with the direct firm-level efficiency gains due to the use of robots, raises the industry's aggregate productivity.

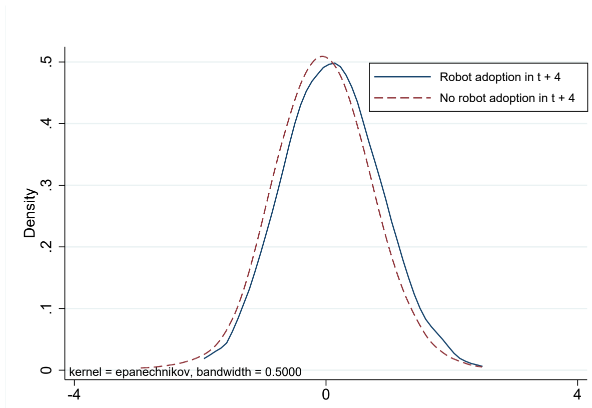
4 Which firms adopt robots?

We now turn to our empirical analysis and begin by investigating which firm-specific characteristics influence the decision to adopt robots. Identifying whether positive selection of more efficient and larger firms is at work in the data can help in understanding the large and persistent productivity differences across firms within industries (Syverson, 2011). In fact, if we find evidence for negative selection in the data, then this would point towards an alternative scenario with a potential catching-up of low-productivity firms through the use of robot technology.[29]

Figure 5: Distribution of base year output and productivity for robot adopters vs. non-adopters



(a) Base year output



(b) Base year labor productivity

Notes: In the left panel, the dashed red line shows the empirical probability density function of base year output of firms that do not use robots when they first appear in the sample at time t and will not have adopted robots four years later, i.e. at time $t+4$. The solid blue line shows the same function of base year output of firms that do not use robots when they first appear in the sample at time t but will have adopted robots four years later (i.e. at time $t+4$). The base year output is given in logs, deflated, and demeaned by industry and year. The right panel shows the same as the left panel but for labor productivity instead of output. The base year labor productivity is given by the log of (deflated) value added per worker demeaned by industry and year.

Before analyzing robot adoption more formally, we use our data to provide graphical evidence on the relationship between firm size/productivity and robot adoption. The left panel of Figure 5 plots the distribution of base year output (deflated and in logs) for robot adopters vs. non-adopters, i.e., for firms that have adopted robots four years after they first appear in the sample vs. firms that

[29]One argument implying negative selection is that more efficient firms are larger and thus require a more complex degree of bureaucracy that can hamper decision making about new technology and skills.

have not adopted robots. The figure reveals that the distribution of robot adopters (solid blue line) clearly dominates the distribution of non-adopters (dashed red line). Since we compute our measure of output relative to the year specific industry mean, differences in firm size across industries are not driving this observation.[30] Moreover, firms using robots already in the base year are not included in the figure, so the differences that we see are not explained by the *effects* of adopting robots. Importantly, we get a similar picture when using base year labor productivity instead of output, i.e., the productivity distribution of robot adopters clearly dominates the one of non-adopters; see the right panel of Figure 5.

We now proceed by investigating the adoption decision through the use of regression analysis. Equation A.5 in online Appendix A.6.1 and the discussion in subsection 3.2.1 reveal that a firm i adopts robots if the profit gain from doing so exceeds the fixed cost of robot adoption. That is firms adopt robots if $\pi_i^a - \pi_i \geq F^a$ and thus $\text{Robot}_i^* = \pi_i^a - \pi_i - F^a$. Hence, the binary outcome of the adoption decision denoted by Robot_i can be understood as reflecting a threshold rule for an underlying latent variable (denoted by an asterisk).[31] We also account for the increase in the supply and quality of robots, as well as the evolution of wages and adoption costs that can change the incentives to adopt robots over time, by including industry-base-year fixed effects given by μ_{s0}. Under these assumptions, we adopt the following basic empirical framework to describe the decision of firms to adopt robots:

$$\text{Robots}_i = \beta\phi_{i0} + \boldsymbol{\gamma}\mathbf{F}_{i0} + \boldsymbol{\delta}\mathbf{G}_{i0} + \mu_{s0} + \varepsilon_i, \tag{2}$$

where the dependent variable is a 0/1 indicator variable for robot use in the production process of firm i equal to one if the firm adopts robots during our sample period and zero otherwise, and where we focus on different sets of explanatory variables: (1) a firm-specific size or productivity variable in the year of sample entry ϕ_{i0}; (2) a vector of factor intensity variables in the year of sample entry $\mathbf{F}_{i0}$; and (3) a vector of globalization variables in the year of sample entry $\mathbf{G}_{i0}$ (with corresponding parameters to be estimated collected in β, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$, respectively). Finally, ε_i is the error term.

The firm's size (productivity) is measured as the log of firm's deflated output value (deflated labor productivity given by the firm's value added per worker). The factor intensity variables we use are the firm's capital intensity, R&D intensity, skill intensity as well as the share of manufacturing employment and the share of production workers (all in logs). Thereby, as argued in subsection 3.2.3, skill intensity can be used as a proxy for the complexity of the production process which determines a firm's likelihood of robot adoption. In addition, we also use different classifications of workers available in the ESEE data-set. While the data does not allow to distinguish among specific occupations, firms are asked to report the share of employment in manufacturing plants (as well as non-manufacturing plants). Secondly, they classify the workforce into production workers and employees & auxiliaries (e.g. managers, technicians, office workers, salesmen, auxiliaries, cleaners).

[30] As we demean by industry-year, we also control for the fact that sample entry of robot adopters might be more likely in years in which all entrants were larger on average.

[31] Specifically, we have $\text{Robot}_i = 1$ (robot adoption) if $\text{Robot}_i^* \geq 0$ and $\text{Robot}_i = 0$ (no adoption) if $\text{Robot}_i^* < 0$.

Arguably, we expect firms to install robots in the production process when they have a high share of manufacturing employment and production workers, which we therefore use as further proxies for the complexity of the production process. Additionally, we also use the share of temporary workers, since these workers might be easier to substitute. The globalization variables we use are 0/1 indicator variables for whether the firm is an exporter, an importer, a foreign-owned firm and if the firm adopts foreign technologies (see the discussion in subsection 3.2.2).[32]

In Table 1 we present OLS estimates of Eq. (2). Standard errors are robust to arbitrary forms of heteroskedasticity. In column (1) we use the most parsimonious specification including output as the only explanatory variable alongside capital and R&D intensity and industry-base-year fixed effects as control variables. In columns (2) and (3) we augment the specification to include our proxies for the complexity of the production process and globalization variables, respectively, and in column (4) we include all variables simultaneously. Finally, throughout columns (5) to (7) we add labor productivity, average wage and the interest rate as further control variables for the efficiency of firms and their labor and capital costs, respectively. Adding these controls does little to our findings. Throughout all columns our estimates provide evidence that larger firms are significantly more likely to adopt robots. This is in line with our previous observation that the output and labor productivity distributions of robot adopters dominate those of non-adopters already before first-time adoption. The average estimated coefficient across all specifications is around +0.04 and implies that an increase by one standard deviation in the firm's base year output raises its probability of subsequently adopting robots by 7 percentage points.

Looking at other selection variables, we find that the skill intensity enters negatively and significantly. This finding is consistent with the idea that higher skill requirements in the production process reduce the scope for economic benefits through robotization. Similarly, the positive and significant coefficients of the share of manufacturing and production workers reveal higher gains from robot adoption for firms employing more workers in these activities. The coefficient of the firm's export status is positive and significant throughout all specifications. It implies that exporting makes firms 3 to 5 percentage points more likely to adopt robots later on (controlling for size, factor intensities, and other globalization variables). These results provide compelling evidence for a fundamental complementarity between exporting and robot adoption at the firm level. Those firms active on international markets through exporting are considerably more likely to adopt advanced technology in the form of robots.[33]

[32]Trade liberalization might also intensify competition and increases the pressure of productivity enhancing investments (see above). The data does not provide firm-specific measures for import competition. However, as long as all firms within an industry face the same degree of import competition, this is captured by the industry-base year controls.

[33]In an alternative specification we have used information on the number of international markets instead of the export indicator. Again, we find evidence that firms selling to more markets are more likely to adopt robots. We also run regressions similar to columns (1) to (4) where we focus on labor productivity as the main selection control for productivity. What is interesting is that estimated coefficients on globalization variables are larger and of higher significance when using firm labor productivity instead of output. Since exporting firms serve a larger market than non-exporting firms, this is evidence that the scale of operations is a critical channel through which globalization supports robot adoption.

Table 1: Selection into robot adoption: Cross-sectional specification

	Robot adoption (0/1 indicator)						
Base year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output	0.0355***	0.0401***	0.0300***	0.0342***	0.0378***	0.0401***	0.0448***
	(0.00520)	(0.00589)	(0.00604)	(0.00660)	(0.00705)	(0.00733)	(0.00966)
Labor productivity					-0.0134	-0.0066	0.0139
					(0.0116)	(0.0123)	(0.0181)
Skill intensity		-0.323***		-0.326**	-0.357***	-0.346***	-0.224
		(0.125)		(0.130)	(0.130)	(0.130)	(0.148)
Share of manu-facturing workers		0.238**		0.231*	0.230*	0.231*	0.249*
		(0.114)		(0.120)	(0.120)	(0.121)	(0.137)
Share of production workers		0.0459*		0.0420*	0.0422*	0.0388	0.0250
		(0.0237)		(0.0245)	(0.0247)	(0.0249)	(0.0319)
Exporter			0.0319**	0.0311*	0.0315*	0.0325**	0.0554***
			(0.0158)	(0.0163)	(0.0163)	(0.0164)	(0.0211)
Assimilation of foreign technologies			0.0467**	0.0320	0.0290	0.0284	-0.00597
			(0.0237)	(0.0244)	(0.0246)	(0.0246)	(0.0371)
Importer			0.00494	0.0123	0.00961	0.00767	0.00466
			(0.0157)	(0.0165)	(0.0166)	(0.0166)	(0.0230)
Foreign owned			-0.0292	-0.0332	-0.0388	-0.0385	-0.0628
			(0.0292)	(0.0298)	(0.0301)	(0.0303)	(0.0425)
Capital intensity	0.0173***	0.0159**	0.0166**	0.0157**	0.0164**	0.0176**	0.0123
	(0.00645)	(0.00683)	(0.00653)	(0.00691)	(0.00705)	(0.00716)	(0.00890)
R&D intensity	0.0173	0.0285	0.00309	0.0157	0.0165	0.0161	-0.0173
	(0.0195)	(0.0203)	(0.0200)	(0.0208)	(0.0212)	(0.0213)	(0.0241)
Average wage						-0.0337	-0.0878***
						(0.0227)	(0.0331)
Interest rate							0.0001
							(0.0037)
Observations	3551	3374	3440	3268	3230	3213	1504
R-squared	0.152	0.157	0.151	0.154	0.158	0.158	0.205

Notes: The dependent variable in all columns is a 0/1 indicator variable equal to one if the firm adopts robots during our sample period and zero otherwise. Output is the firm's deflated output value (in logs). Labor productivity is the firm's deflated value added per worker (in logs). Skill intensity is the firm's share of workers with a five-year university degree (in logs). Share manufacturing is the firm's share of manufacturing workers (in logs). Share production is the firm's share of production workers (in logs). Exporter is a dummy variable for positive exports. Assimilation of foreign technologies is a dummy variable indicating whether the firm assimilated foreign technologies. Importer is a dummy variable for positive imports. Foreign owned is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Capital intensity is defined as the firm's deflated capital stock per worker (in logs). R&D intensity is defined as the firm's deflated R&D expenditures relative to its deflated total sales (in logs). Average wage is defined as the firm's labor costs divided by the total number of workers (in logs). Interest rate is defined as the firm's interest rate on short-term dept (in percent). All estimates include industry-base-year fixed effects. We add one to all factor intensity variables before taking logs in order to keep zero observations. Therefore, all estimates include dummy variables (not reported) equal to one whenever the respective factor intensity variable is equal to zero before adding one. All explanatory variables are measured in the base year defined as the first year the firm appears in the sample. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

We have verified the *econometric robustness* of our results by employing a variety of different estimators and model specifications. Doing full justice to the binary nature of our robot adoption variable, we estimate a non-linear Probit model; see Table A.6 in online Appendix A.7. Employing a more flexible model specification and allowing for non-linearity and non-monotonicity in the effects of output on robot adoption, we find that firms in the top quartile of the output distribution have the highest probability of adopting robots; see Table A.7 in online Appendix A.7. Extending the analysis to a panel version of Eq. 2, we find a picture that largely resembles our cross-sectional estimates; see Table A.8 in online Appendix A.7.[34]

A different question, unrelated to the econometric robustness of our results, is whether and to what extent *employment protection legislation* has a bearing on a firm's robot adoption decision. Intuitively, firms might shy away from adopting robots due to high degrees of employment protection, which makes it difficult or impossible for firms to lay off workers that would otherwise be replaced by robots. The ESEE data does not provide explicit information on firm-specific employment protection or bargaining agreements. Such measures are only available at the level of the industry and are thus controlled for by our industry-year fixed effects. As an inverse measure of employment protection at the firm level, we therefore use the share of temporary workers reported by firms. Dolado et al. (2002) document that Spain increased the possibilities for hiring and firing temporary workers during the 1980s and 1990s resulting in one of the highest shares of temporary workers in Europe. In our data set the share across industries varies between 9% (in Chemical & Pharmaceutical Products) and 28% (in Leather & Footwear). We include the share of temporary workers as an additional firm-level control in our regression analysis, expecting that higher shares raise the likelihood of robot adoption. However, in none of the specifications is the estimated coefficient different from zero (in a statistical sense); see Table A.9 in online Appendix A.7.

5 The effects of robot adoption

We now aim to identify the consequences of robot adoption at the firm level. Our focus here is on the effects on output, as well as on employment, labor costs, and average wages before we turn towards a structural approach on the TFP gains from robot adoption in section 6.

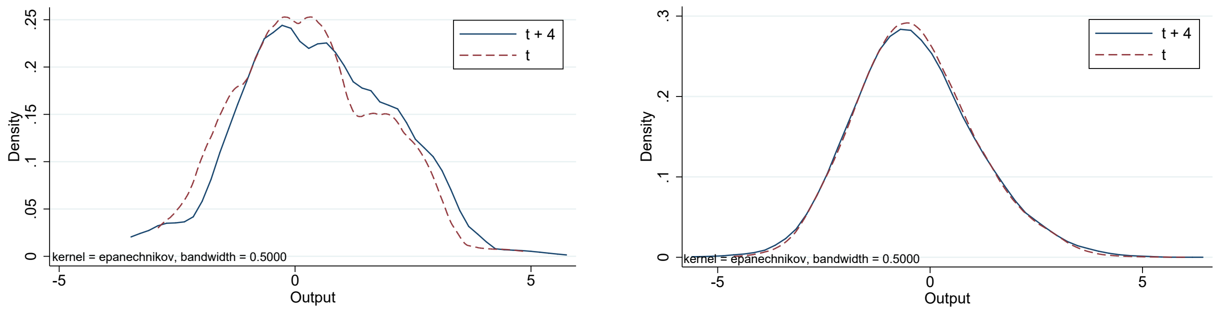
5.1 Output effects

We first present graphical evidence on the output distribution of robot adopters before and after the adoption, and benchmark it against changes in the output distribution of non-adopters. Figure 6 provides a first indication that, in contrast to non-adopters, robot adopters were able to significantly expand the scale of their operations. The left panel makes a before-after comparison among robot adopters. It reveals that the distribution of output (deflated and in logs) when firms enter the sample in t (dashed red line) is clearly dominated by the distribution of output four years later

[34] To allow for time-varying measures of our selection variables, we estimate a panel specification of the form $\text{Robots}_{it} = \beta\phi_{it-1} + \boldsymbol{\gamma}\mathbf{F}_{it-1} + \boldsymbol{\delta}\mathbf{G}_{it-1} + \mu_{st} + \varepsilon_{it}$, where the regressors are lagged by one year and μ_{st} is an industry-year fixed effect.

at $t+4$ (solid blue line) when the same firms have adopted robots. The right panel makes the same comparison for firms that do not adopt robots and reveals almost no differences in the output distribution.

Figure 6: Before-after comparison of the output distribution for robot adopters



(a) Robot adopters

(b) Non-adopters

Notes: The left panel makes a before-after comparison of the output distribution of robot adopters, i.e., firms that do not use robots when they first appear in the sample at time t, but will have adopted robots four years later (i.e. at time $t+4$). The red dashed line and the solid blue line show the empirical probability density function of output at time t and at time $t+4$, respectively. The right panel makes the same comparison for non-adopters, i.e., firms that do not use robots when they first appear in the sample at time t and will not have adopted robots four years later (i.e. at time $t+4$). Output is given in logs, deflated, and demeaned by industry.

To identify the effect of robot adoption on firm-level output more formally, we estimate the following equation:

$$\text{Output}_{it} = \gamma_1 \text{Robots}_{it} + \gamma_2 \text{Robots}_{it-4} + \boldsymbol{\beta}\mathbf{X}_{it-4} + \mu_i + \mu_{st} + \varepsilon_{it}, \tag{3}$$

where the dependent variable is deflated output of firm i in year t (in logs), $\mathbf{X}_{it-4}$ is a vector of time-varying firm-level controls lagged by four years, with a corresponding vector of parameters $\boldsymbol{\beta}$ to be estimated, μ_i and μ_{st} are firm and industry-year fixed effects, respectively, and ε_{it} is an error term with zero conditional mean. The parameter μ_{st} captures general time trends and industry shocks affecting firms equally within industries. The parameters of interest in (3) are γ_1 and γ_2, both capturing the impact of robot adoption on firm-level output. These parameters indicate the percentage change in output after firms start using robots in their production process.

By including fixed effects for individual firms, we identify the output effects of robot adoption only through within-firm variation, i.e., firms switching from non-robot use to robot use over time. The firm fixed effects control for robot adoption based on time-invariant factors, like the firm's baseline productivity $\phi(\omega)$ in our theoretical framework. To control for robot adoption based on not just time-invariant but also time-varying firm-level variables, we include labor productivity, capital intensity, skill intensity, R&D intensity (all in logs), as well as indicator variables for exporting, importing, and foreign ownership in $\mathbf{X}_{it-4}$.[35] We also estimate specifications including the four-

[35] We let the firm-level control variables enter with a four-year lag in order to control for selection into robot adoption in $t-4$ and t. However, we have also used a one-year lag instead of a four-year lag, to find that this does not alter our estimates in any significant way.

year forward of our robot indicator variable (Robots_{it+4}). This allows us to see whether our model is reasonably successful at controlling for positive selection into robot adoption as identified in the previous section.

To make further progress in establishing a causal effect of robot adoption on output, we closely follow the empirical methodology proposed by Guadalupe et al. (2012) and combine the firm fixed effects approach with a propensity score reweighting estimator in the spirit of DiNardo et al. (1996). Specifically, we construct propensity scores and reweigh each firm in order to generate a similar distribution of key observable characteristics across robot adopters and non-adopters. By matching along observable firm characteristics, we hope to also match the distribution of important unobservable characteristics. To estimate the propensity scores, we consider the years 1991, 1994, 1998, ..., 2014 in our panel and sort those firms that adopt robots in that year into the treatment group and those that never use robots into the control group. We then pool observations in the treatment and in the control group across all these years and obtain the propensity scores for all firms by running industry-specific probit regressions for robot adoption (the treatment) on one-year lags of sales, sales growth, labor productivity, labor productivity growth, capital-, skill- and R&D-intensity, indicators for exporter, importer and foreign ownership, and year dummies.[36] The growth rates of both labor productivity and sales control for recent performance differences among firms. We then use the estimated propensity scores and reweigh each treated firm by $1/\hat{p}$ and each control firm by $1/(1-\hat{p})$, where $\hat{p}$ is the estimated propensity score.[37]

Table 2 shows our estimates of Eq. (3). We first estimate the equation with firm fixed effects, but without selection controls (columns (1) and (2)); we then add time-varying firm-specific variables as selection controls (columns (3) and (4)); and we finally use the propensity score reweighting estimator as described above (columns (5) and (6)). We estimate each of the three variants with and without the four-year forward of the robot indicator variable. Throughout all specifications employed, we find positive and significant output effects of robot adoption. We also see that, once we include selection control variables or use the propensity score reweighting estimator to control for positive selection into robot adoption, the four-year forward of the robot indicator variable is not significantly different from zero. This makes us confident that, for our purposes, we are modelling the selection decision reasonably well.[38] To get a sense of the magnitude of the effects, consider the

[36]In the online Appendix, we report estimates using additional selection controls when obtaining propensity scores. In a first step, we add the value of the firm's capital stock, investments in machinery and the stock of process innovations in computer programs attached to manufacturing processes. These variables increase prior to the adoption of robots as revealed in our event-study analysis in section 2. In a second step, we furthermore add the share of manufacturing workers as a proxy for the complexity of the production process, see Tables A.15 and A.16.

[37]We only keep those observations in the analysis that are in the region of common support, and we have checked that the balancing property is supported by the data in all industries, i.e., all observed characteristics of robot adopters and non-adopters are balanced. More output corresponding to the propensity score estimation can be found in Table A.12 in online Appendix A.9.

[38]If the coefficient of the four-year forward robot indicator is significantly different from zero, then there are some anticipatory effects and the pre-treatment is affected by current treatment. That is, firms anticipate robot adoption in the future and start to adjust accordingly. Furthermore, if the coefficient is significantly different from zero, then the robot adoption effect in the current period can not be interpreted as causal (see Autor, 2003). Since our coefficients of the four-year forward robot indicator are not different from zero (in a statistical sense), indeed, we can claim that there

Table 2: Output effects of robot adoption

	Output (in logs)					
	(1)	(2)	(3)	(4)	(5)	(6)
Robots_t	0.155***	0.110***	0.161***	0.120***	0.123***	0.115**
	(0.0292)	(0.0349)	(0.0314)	(0.0371)	(0.0390)	(0.0507)
Robots_{t-4}	0.121***	0.127***	0.118***	0.105**	0.119***	0.0764
	(0.0321)	(0.0447)	(0.0336)	(0.0476)	(0.0412)	(0.0550)
Robots_{t+4}		0.0725**		0.0466		0.0747
		(0.0353)		(0.0383)		(0.0490)
Observations	4965	2799	4573	2571	4621	2627
R-squared	0.239	0.298	0.249	0.294	0.266	0.287
Selection controls	No	No	Yes	Yes	No	No
Propensity scores	No	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. The dependent variable in all columns is the log of the firm's deflated output value. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

estimates of γ_1 and γ_2 in column (5), which are equal to +0.126 and +0.121, respectively. These estimates imply that the adoption of robots in the production process raise output by almost 25% within four years.[39,40]

5.2 Labor market effects

We now turn to the labor market effects of robot adoption at the firm level. Specifically, we consider the effects on the firm's employment (for specific groups of workers and overall), the labor cost share, and the average wage. Our theoretical considerations in the previous section imply that robot adopters will reduce their labor cost share, while the impact on total employment is ambiguous and depends on the relative strength of the displacement effect and the productivity effect. The employment effects might also be specific to certain groups of workers, especially to those performing automatable tasks (low-skilled workers as well as workers in the firm's manufacturing rather than service-oriented establishments). As for the wage effects, our theoretical framework implies that the average wage in firms adopting robots increases if the firm changes the composition of its workforce

are no anticipatory trends and from a diff-in-diff perspective, a necessary condition for the parallel trend assumption holds.

[39]Since we have robot information available in our data, not every year, but every four years, there is some uncertainty regarding the precise timing of first time robot adoption. A firm that reports robot use in $t-4$, but no robot use in $t-8$, can have adopted robots for the first time in either $t-4$, $t-5$, $t-6$, or $t-7$. Hence, the most conservative interpretation is that the adoption of robots raises output by almost 25% within seven years.

[40]In an additional set of estimates, we investigate whether the output gains from robot adoption are more pronounced in firms that are more integrated into the global economy. We do not find robust evidence that exporters (or importers or foreign-owned firms) experience stronger output gains from adopting robots. Furthermore, we do not find evidence that robot adoption increases the probability to start exporting or the share of exports in total sales.

by hiring relatively more high-skilled workers (and given a positive exogenous skill premium). To shed light on these effects, we estimate an equation akin to Eq. (3), where we use a variety of different labor market variables as dependent variables. Table 3 reports the results. In Panel A we control for selection into robot adoption by including the same set of time-varying selection controls as before. In Panel B we combine the firm fixed effects estimator with our propensity score weighting approach. All models include firm and industry-year fixed effects.

A striking result in Panel A in Table 3 is that within four years robot adopters raise overall employment by around 10 percent. Importantly, this applies to all types of workers, low- and high-skilled workers as well as workers employed in the firm's manufacturing establishments. Moreover, while the labor cost share decreases significantly due to robot adoption, by almost 7 percentage points, we find no significant effect on the firm's average wage, although the coefficient is estimated with a negative sign. The results based on the propensity score estimates in Panel B, by and large, confirm these results, although the positive employment effects for the group of high-skilled workers are smaller in magnitude and lose significance.

Even though our results indicate a positive impact of robot adoption on overall employment, the adoption might be seen as a disruptive event on employment within firms. To further shed light onto the firm level employment effects, we use information available in the ESEE survey data on workforce reductions that have the flavor of collective dismissals. The additional survey question that we now exploit in our analysis contains explicit information on the change in regular workers due to redundancies. Specifically, the survey asks firms (yes/no) whether there has been a significant change in the regular workforce due to a "reduction in the workforce (termination of con-tracts, early retirement, incentives for leaves of absence, etc.)" over the last year. We use this information to construct an indicator variable equal to one if there was a significant change in the current year. In a first step, we investigate whether robot adoption is associated with an increase in the likelihood of collective dismissals. Results indicate no statistically significant and robust relationship between robot adoption and collective dismissals. In a second step, we include the indicator variable for collective dismissals in the current and previous years as further control variables in the estimates akin to Table 3. Including them does very little to our estimated effects of robot adoption on different labor market outcomes. Not surprising, the estimated coefficients for collective dismissals reveal a negative effect on employment, which is concentrated among low-skilled and manufacturing workers. To safe on space we present regression details to these additional set of estimates in the online Appendix of this paper (see subsection A.13).

We furthermore investigate if the positive employment effects documented in Table 3 especially arise for exporting firms, as only exporting firms might face sufficient demand that compensates for the substitution of workers for robots. We therefore augmented the specification and added an interaction term between robot use and exporter status (both, in t and $t-4$). Results to this are reported in Tables A.13 and A.14 in online Appendix A.10. While exporters are larger and more skill- and manufacturing intensive, it turns out that the positive employment effects are not limited to exporting firms, as none of the interaction terms turn out to be significantly different from zero. Only the reduction in the labor cost share turns out to be more pronounced for exporting firms. Furthermore, including the export indicators and the interaction term between robot use and exporter status (both, in t and $t-4$) reduces significance of the robot indicator. This already speaks to a potential complementarity, such that firms jointly decide on robot adoption and export entry, and we investigate these dynamics in greater detail in Section 6.[41]

[41] In online Appendix A.11 we present results on the effects of alternative systems in the production process, namely computer-digital machine tools (CAM), computer-assisted design (CAD), and a combination of some of the systems through a central computer (FLEX). It turns out that output and labor market effects of robot adoption reported above are fully robust to controlling for such alternative systems in the production process. Secondly, while CAM and FLEX increase firm output, the effects are smaller in magnitude than in the case of robot adoption. Thirdly, there is evidence for positive employment effects across all three technologies (CAD, CAM, and FLEX) and in all skill groups. Finally, we identify a striking difference between robot technology and other technologies used in the firm's production process: only robots lead to a significant reduction in the firm's labor cost share.

Table 3: Labor market effects of robot adoption

	Employment	Labor cost share	Low-skilled	High-skilled	Manufacturing employment	Share of manuf. employment	Average wage
PANEL A: Selection Controls	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)
Robots$_t$	0.0584**	-0.0359***	0.0597**	0.0796**	0.0413	-0.00662	-0.00247
	(0.0251)	(0.00880)	(0.0260)	(0.0383)	(0.0279)	(0.00566)	(0.0117)
Robots$_{t-4}$	0.0527**	-0.0318***	0.0410	0.106***	0.0494*	-0.00493	-0.0156
	(0.0245)	(0.0109)	(0.0252)	(0.0379)	(0.0259)	(0.00516)	(0.0160)
Observations	4575	4544	4552	4552	4568	4568	4535
R-squared	0.201	0.158	0.209	0.140	0.203	0.062	0.615
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PANEL B: Propensity Score	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)
Robots$_t$	0.0591**	-0.0242**	0.0708**	0.0564	0.0508*	-0.00338	0.00934
	(0.0276)	(0.0113)	(0.0286)	(0.0432)	(0.0290)	(0.00476)	(0.0171)
Robots$_{t-4}$	0.0656*	-0.0276**	0.0658*	0.0543	0.0642*	-0.00474	-0.0151
	(0.0351)	(0.0138)	(0.0350)	(0.0492)	(0.0349)	(0.00498)	(0.0185)
Observations	4620	4583	4599	4599	4612	4612	4573
R-squared	0.212	0.204	0.226	0.158	0.242	0.129	0.664
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

5.3 Looking at non-adopting firms

As argued in subsection 3.3.2, robot adopting firms gain market shares prompting the least productive firms to exit, and the surviving non-robot firms to reduce their output and employment. To estimate this last set of predictions from our theoretical model, we now estimate the effects of robot diffusion within industries on non-adopting firms. To do so, we estimate variants of the following equation:

$$\text{Outcome}_{it} = \gamma_1 \text{Robot-density}_{st} + \gamma_2 \text{Robot-density}_{st} \times \text{Robots}_{it} + \gamma_3 \text{Robots}_{it} + \boldsymbol{\beta_1} \mathbf{X}_{it-4} + \mu_i + \mu_t + \varepsilon_{it}, \tag{4}$$

where we use firm-level employment, output, and market exit as different outcomes of firm i at time t, and where we interact a time-varying industry-specific measure of robot density with a time-specific firm-level dummy variable for the use of robots. The variable Robot-density$_{st}$ is constructed in two different ways using two different data-sets. First, we use our ESEE data-set and define the variable as the share of sales attributable to robot-using firms in total industry sales.[42,43] This measure is only available in those years in which we have information on robot use in the survey (i.e. every four years). In an alternative approach, we use data from the International Federation of Robotics (IFR) and more specifically the industry-specific stock of robots over the period 1993 to 2016. This measure of robot density is available on an annual basis and features yearly variation. The variable Robots$_{it}$ in Eq. (4) is a 0/1 indicator variable equal to one if the firm uses robots in the specific period, and zero otherwise.

The coefficients of interest are γ_1, γ_2 and γ_3. The first coefficient tells us the effect of rising robot density in an industry on non-adopting firms, while the second and third coefficient tells us the difference in the effect of robot density on robot users vs. non-adopters. In Panel A and B of Table 4 we report estimates when using output and employment as an outcome variable, respectively, while Table A.17 in the online Appendix reports estimates when looking at market exit.[44] In columns (1) to (3) and columns (4) to (6), we use our robot density measure from the ESEE data and the IFR data, respectively. All specifications include both firm fixed effects (μ_i) and year fixed effects (μ_t). In columns (2) and (5) we include our selection controls for robot adoption in the vector $\mathbf{X}_{it-4}$ (see Section 4). To make sure that our results are indeed due to differences in robot density across industries, and not other important industry-specific factors, we also augment the model by including time-varying industry-specific factor intensity variables (namely annual industry averages of capital, skill, and R&D intensity), and we also interact these variables with our firm-level indicator variable for robot use. Finally, for the estimates on employment and output we also

[42] We have verified that our results are robust to alternative definitions of this variable using the ESEE data, viz. the share of robot-using firms in the total number of firms, the share of output attributable to robot-using firms in industry output, and the share of employment in robot-using firms in total industry employment.

[43] To construct meaningful measures of robot density, when computing this variable, we do not restrict the sample to firms that do not use robots in the first year they appear in the sample, while for the estimation we use the restricted data-set. However, we have verified that our results do not change when we also use the full sample of firms in the estimation.

[44] Firms might disappear from the sample due to either exit (in the form of shutdown by death or abandonment of activity) or attrition, which can be distinguished in the data (see Doraszelski and Jaumandreu, 2013, p.1343).

allow the (4-years) lagged dependent variable to enter the right-hand-side of equation 4 in columns (3) and (6).

Table 4: Robot adoption and intra-industry reallocations

	ESEE			IFR		
PANEL A: Employment in t	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)
Robot-density$_t$	-0.158***	-0.184***	-0.203***	-0.00822	-0.00877	-0.0169
	(0.0451)	(0.0655)	(0.0563)	(0.0124)	(0.0166)	(0.0119)
Robot-density$_t$ × Robots$_t$	0.156	0.320***	0.235***	0.0349***	0.0397***	0.0260***
	(0.106)	(0.122)	(0.0884)	(0.00999)	(0.0139)	(0.0100)
Robots$_t$	0.0111	-0.124	-0.118*	-0.150**	-0.157*	-0.130*
	(0.0443)	(0.0791)	(0.0655)	(0.0605)	(0.0902)	(0.0739)
Observations	10126	4577	4577	8358	4388	4388
R-squared	0.089	0.133	0.288	0.118	0.136	0.283
PANEL B: Output in t	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)
Robot-density$_t$	-0.232***	-0.275***	-0.229***	-0.0164	-0.0152	-0.0158
	(0.0582)	(0.0871)	(0.0795)	(0.0158)	(0.0204)	(0.0162)
Robot-density$_t$ × Robots$_t$	0.478***	0.490***	0.350***	0.0482***	0.0528***	0.0334**
	(0.119)	(0.142)	(0.125)	(0.0131)	(0.0162)	(0.0135)
Robots$_t$	-0.0214	-0.184*	-0.145	-0.144*	-0.166	-0.104
	(0.0497)	(0.112)	(0.101)	(0.0822)	(0.122)	(0.105)
Observations	10168	4575	4575	8341	4384	4384
R-squared	0.139	0.161	0.266	0.159	0.160	0.260
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Selection controls	No	Yes	Yes	No	Yes	Yes
Industry controls + interact.	No	Yes	Yes	No	Yes	Yes
Lagged dependent variable	No	No	Yes	No	No	Yes

Notes: In columns (1) to (3) we define robot density as the share of sales attributable to robot-using firms in total industry sales constructed from the ESEE data. In columns (4) to (6) we use the stock of robots in an industry (in logs) constructed from the IFR data. The variable robots is a 0/1 indicator variable equal to one if the firm uses robots in the sample year, and zero otherwise. In Panels A and B we use employment and deflated output (both in logs) as the dependent variables, respectively. Selection controls include the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), exporter status, importer status, and foreign ownership status (all in *t-4*). We add one to all factor intensity variables before taking logs in order to keep zero observations. Industry controls are annual industry averages of capital, skill, and R&D intensity; these variable are also interacted with the firm-specific robot-use dummy variable. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

The negative estimates of γ_1 in Panel A of Table 4 show that an increase in robot density has a significantly negative impact on employment in firms that do not adopt robot technology. The estimates in the first three columns imply that 10% of jobs in non-adopting firms are destroyed when the share of sales attributable to robot-using firms increases from zero to one-half. Importantly, the positive and significant estimates of γ_2 indicate that these effects are exclusive to non-adopters. Looking at Panel B, we see the same pattern of effects in terms of output, but the implied magnitude is even more pronounced. Looking at Table A.17, we document some weak evidence of higher exit rates among non-adopters due to an increase in robot density, which is consistent with the predicted increase in the survival cut-off productivity in our theoretical framework. Importantly, we find similar results on employment, output, and exit rates when using the stock of robots within industries from the IFR data. This is remarkable because the IFR measure captures the intensive margin of robot diffusion, regardless of how many firms use this technology, whereas the ESEE measure reflects the share of firms using robots and thus the extensive margin of robot use.

When interpreting the results presented in Tables 4 and A.17 one should keep in mind that they are not based on the entire number of firms, and reallocation effects might clearly extend beyond industry boundaries. That is, in the empirical analysis we implicitly assume that firms active in different industries are independent from each other, which is violated due to input-output linkages and competition within specific labor markets or regions. Nevertheless, the results provide support for the idea that robot adopters expand their scale of operations and create jobs, while non-adopters experience negative output and employment effects in the face of tougher competition with high-technology firms. Our results thus imply intra-industry reallocation of market shares and resources as a result of more widespread diffusion of robot technology and a polarization between high-productivity robot adopters and low-productivity non-adopters, which also finds recent support in Acemoglu et al. (2020).

6 Robots and firm-level productivity

In the last part of our analysis, we want to investigate the possibility that firms improve their performance (productivity) through automation using a structural estimation approach. We borrow this approach from the literature dealing with production function estimates. Our focus is on the role of robots in shaping a firm's future productivity, and our goal is to establish the productivity gain associated with firms adopting robots in the production process. We will do this by explicitly allowing the evolution of productivity to depend on prior use of robots in the production process. For this purpose, we will accommodate endogenous productivity processes in the spirit of De Loecker (2013), who applied this approach in the context of learning by exporting.

6.1 Empirical framework

Following the literature, we consider a Cobb-Douglas production function (in logs) for firm i at time t producing output (y_{it}) from labor (l_{it}) and capital (k_{it}):

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it}, \tag{5}$$

where ω_{it} reflects the firm's productivity (including a constant term) and ε_{it} is an i.i.d. error term.[45] In our set-up, the use of robots in the production process is allowed to impact future productivity as given by

$$\omega_{it+1} = E[\omega_{it+1}|\omega_{it}, \text{Robots}_{it}] + \xi_{it+1} = g(\omega_{it}, \text{Robots}_{it}) + \xi_{it+1}, \tag{6}$$

[45] Our approach shares a standard set of assumptions with the literature; see Ackerberg et al. (2007) and De Loecker (2013) for details.

where Robots_{it} is a 0/1 indicator variable for robot use in the (endogenous) production process of firm i at time t.[46,47] Hence, *actual* productivity in period $t+1$ can be decomposed into *expected* productivity $g(\omega_{it}, \text{Robots}_{it})$ and a random shock ξ_{it+1}. Importantly, the conditional expectation function $g(\cdot)$ depends, not just on already attained productivity ω_{it}, but also on the use of robots Robots_{it}. The random shock ξ_{it+1}, or *productivity innovation*, captures uncertainties that are naturally linked to productivity plus the uncertainties inherent in the use of robots, such as success in implementation.

The timing of decisions is important. When the decision about robot use is made in period t, the firm is only able to anticipate the expected effect of robots on productivity in period $t+1$ as given by $g(\omega_{it}, \text{Robots}_{it})$. The actual effect also depends on the realization of the productivity innovation ξ_{it+1} that occurs after robots have already been integrated into the production process.[48]

The parameters of interest are identified using the following moment conditions of the productivity innovation ξ_{it+1}:

$$E\left\{\xi_{it+1}(\beta_l, \beta_k)\begin{pmatrix} l_{it} \\ k_{it+1} \end{pmatrix}\right\} = 0. \tag{7}$$

To obtain $\xi_{it+1}(\cdot)$ we regress $\omega_{it+1}(\beta_l, \beta_k)$ on $(\omega_{it}(\beta_l, \beta_k), \text{Robots}_{it})$, and $\omega_{it+1}(\beta_l, \beta_k) = \hat{y}_{it+1} - \beta_l l_{it+1} - \beta_k k_{it+1}$. Predicted output $\hat{y}_{it+1}$ is obtained from a first-stage regression of output on inputs and the proxy variables intermediate inputs, capital, and robot dummy.[49,50]

6.2 Estimates of productivity effects

For the endogenous productivity process, we rely on a third-order polynomial in productivity, interacting all terms with our robot dummy variable. Formally,

$$\omega_{it+1} = \sum_{j=0}^{3} \theta_j \omega_{it}^j + \sum_{k=0}^{3} \vartheta_k \left[\omega_{it}^k \times \text{Robots}_{it}\right] + \xi_{it+1}. \tag{8}$$

[46] The earlier literature on structural identification of productivity uses an *exogenous* first-order Markov process for the productivity evolution (Olley and Pakes, 1996; Levinsohn and Petrin, 2003).

[47] In the actual estimation, we also include an estimated survival probability in the function $g(\cdot)$ to correct for sample selection, as in Olley and Pakes (1996). We omit the term here and in the following to avoid cluttered notation.

[48] The assumption that firms decide on whether to use robots before they learn about the productivity innovation is crucial for identification. Formally, the condition we rely on is $E(\xi_{it+1}\varepsilon_{it}) = 0$.

[49] For the first stage, we write productivity ω_{it} as a function of observables and substitute this into the production function to obtain

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + f_t^{-1}(k_{it}, m_{it}, \text{Robots}_{it}) + \varepsilon_{it},$$

where m_{it} are intermediate inputs and $f_t^{-1}(k_{it}, m_{it}, \text{Robots}_{it})$ is the inverse of the firm's intermediate input demand function.

[50] Descriptive statistics for the full sample of firms we use throughout this section are reported in Table A.4. We measure output as value added (production value minus the value sum of energy purchases, raw materials, and services), suitably deflated with a combined firm-level output and intermediate input price index available in our data; labor as effective work-hours; and capital using the perpetual inventory method and deflated using an industry-level price index.

Table 5 reports estimates of θ and ϑ, looking at the *average* effects for the Spanish manufacturing sector at large. We report the estimates of different specifications for the model, viz. for $j = 1$, $k = 0$ (column (1)), $j = 3$ and $k = 0$ (column (2)), and $j = k = 3$ (column (3)). In addition to a high degree of persistence in productivity (θ_1 close to one), we find evidence that the adoption of robots on average increases firm productivity. The coefficient of the robot dummy variable is small (ϑ_1 between 0.004 and 0.01) but positive and statistically significant at least at the five percent level across all specifications (1) through (3). There is also some evidence that the use of robots interacts with the productivity of the firm, but overall this evidence is not very conclusive; see column (3). In summary, our analysis demonstrates a clear causal effect of robots on firm-level productivity, and thus highlights robot technology as a specific source of productivity gains in the modern economy.

Table 5: Estimates of productivity effects of robots

	(1)	(2)	(3)
Robots_{t-1}	0.00378**	0.00609***	0.0102***
	(0.00181)	(0.00182)	(0.00255)
$\text{Productivity}_{t-1}$	0.995***	0.995***	0.994***
	(0.000492)	(0.00178)	(0.00204)
$\text{Productivity}^2_{t-1}$		-0.00866***	-0.00807***
		(0.00143)	(0.00164)
$\text{Productivity}^3_{t-1}$		-0.00305***	-0.00269***
		(0.000349)	(0.000397)
$\text{Productivity}_{t-1} \times \text{Robots}_{t-1}$			0.00708*
			(0.00426)
$\text{Productivity}^2_{t-1} \times \text{Robots}_{t-1}$			-0.00414
			(0.00346)
$\text{Productivity}^3_{t-1} \times \text{Robots}_{t-1}$			-0.00208**
			(0.000870)
Observations	15372	15372	15372
R-squared	0.997	0.997	0.997

Notes: The table reports estimates of θ and ϑ in Equation (8). The first stage includes labor, capital, materials and robot indicator. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

As is well-known from the trade literature, exporting is another and much-studied activity generating productivity gains for firms (see Wagner, 2007, 2012, for comprehensive surveys of studies using firm-level data). To see whether our results are robust to accounting for exports, and to explore potential interactions with the productivity effects of exporting, we adjust the structural TFP estimation following the approach in Aw et al. (2011) and De Loecker (2013). Specifically, we modify the endogenous productivity process in Eq. (8) to include an export dummy variable, Export_{it}, interacted with the robot dummy (higher-order productivity terms are omitted for simplicity). Thus, exporting *and* the use of robots in the production process are allowed to impact future productivity in Eq. (6).[51] The key message from Table 6 is that robots raise firm-level productivity if, and only if, the robot-adopting firm is also an exporter; see column (1). This finding is in line with our

[51] Here we include labor, capital, intermediate inputs, and the export and robots indicators in the first stage.

results on the link between robot adoption and exporting documented in the previous sections. As exporters serve larger markets than non-exporting firms, this is evidence that the scale of operations is a critical channel through which exporting supports productivity-enhancing innovations within firms (see, for example, Lileeva and Trefler (2010), Aw et al. (2011), and De Loecker (2013)). In terms of quantitative implications, our estimates imply that within exporting firms productivity increases by more than 1.3% one year after the adoption. Column (2) reveals that the positive and significant interaction between exporting and robots is robust to including further interactions among productivity, exports, and robots.

Table 6: Estimates of productivity effects of robots and exports

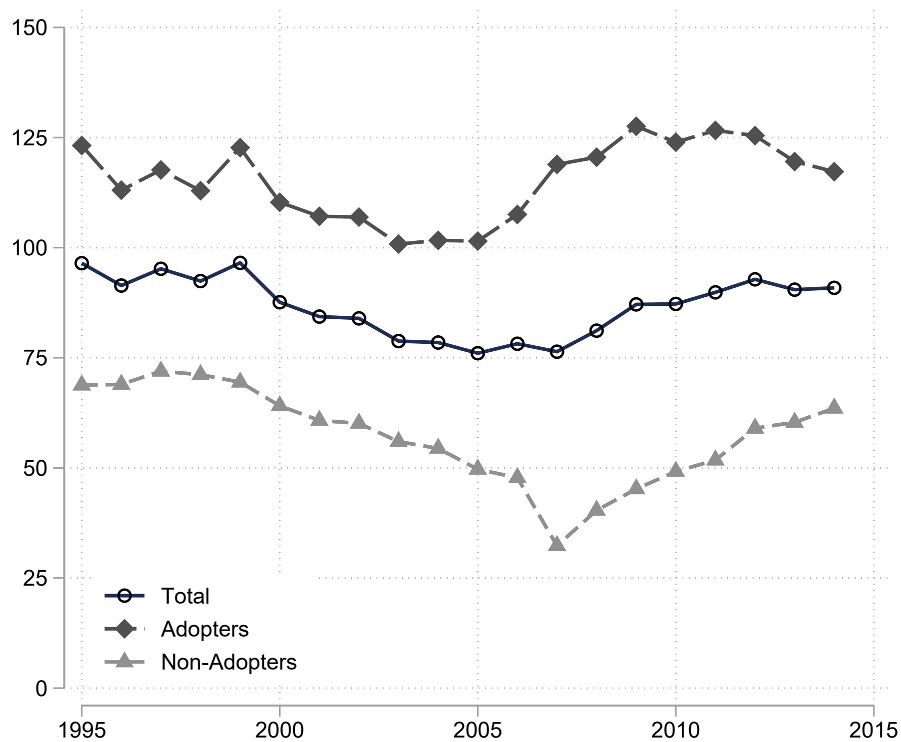
	(1)	(2)
Robots_{t-1}	-0.00345	-0.00331
	(0.00254)	(0.00352)
$\text{Productivity}_{t-1}$	0.994***	0.995***
	(0.00135)	(0.000923)
Export_{t-1}	0.00912***	0.00755**
	(0.00342)	(0.00369)
$\text{Export}_{t-1} \times \text{Robots}_{t-1}$	0.0165**	0.0160**
	(0.00683)	(0.00812)
$\text{Productivity}_{t-1} \times \text{Robots}_{t-1}$		-0.000273
		(0.00290)
$\text{Productivity}_{t-1} \times \text{Export}_{t-1}$		-0.00323
		(0.00329)
$\text{Productivity}_{t-1} \times \text{Export}_{t-1} \times \text{Robots}_{t-1}$		-0.00108
		(0.00706)
R-squared	15349	15349
Observations	0.993	0.993

Notes: *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

6.3 Robots and aggregate TFP in Spain

Finally, we use our structural productivity estimates to visualize the evolution of productivity in Spanish manufacturing across the years 1995 to 2014. As is thoroughly documented by García-Santana et al. (2020), Spanish TFP actually *declined* between 1995 and 2007. The poor productivity performance over this period is an interesting phenomenon in and of itself, not least because this period is also the historically longest uninterrupted period of GDP growth in Spain. To validate our structural estimation approach, we want to see whether this phenomenon is also reflected in our estimates. We find that it is. Specifically, the solid black line in Figure 7 displays the evolution of TFP for the Spanish manufacturing sector at large (TFP is normalized to equal 100 in 1994). Thus, each point in the figure reflects the TFP level relative to its level in 1994, indicating that, between 1994 and 2007, TFP declined by 25%. However, there are interesting between-firm differences in the level and growth of TFP. Across all years, TFP *levels* are consistently higher for robot adopters than for non-adopters. Moreover, TFP *growth* was less negative for robot adopters than for non-adopters up until 2007. In fact, most of the decline in the productivity of Spanish manufacturing in our sample can be attributed to non-adopters. Interestingly, the largest difference in TFP growth between the two groups of firms is visible at the onset of the financial crisis, with robot adopters showing strong *positive* TFP growth, and non-adopters showing strong *negative* TFP growth from 2006 to 2007. However, non-adopters had a markedly better productivity performance between 2007 and 2014 than adopters.

Figure 7: Evolution of TFP in Spanish manufacturing (1995-2014))



Notes: The figure illustrates the evolution of TFP for the Spanish manufacturing sector at large (solid black line), for the group of robot adopters (dark gray dashed line with diamonds) and non-adopters (light gray dashed line with triangles) for the years 1995 to 2014, where TFP is normalized to 100 in the year 1994. Each point reflects the TFP relative to 1994.

7 Conclusion

This paper provides novel evidence on how automation in the form of robot adoption affects firm-level outcomes. We use detailed firm-level information from a survey conducted on Spanish manufacturing firms over a 27-year period (1990-2016). We provide insight into the following central questions: Which firm characteristics have a causal impact on the probability of adopting robots in the production process? What are the implications for output and workers in robot adopting firms relative to non-adopting firms? How does the adoption of robots contribute to the growth in total factor productivity (TFP)? As for the first question, we establish robust evidence that ex-ante larger and more productive firms and exporters are more likely to adopt robots, while, conditional on size, ex-ante more skill-intensive firms are less likely to do so. As for the second question, we find that robot adoption generates substantial output gains in the vicinity of 20-25% within four years, reduces the labor cost share by 5-7%-points, and leads to net job creation at a rate of 10%. We also reveal substantial job losses in firms that do not adopt robots, and thus a productivity-enhancing reallocation of labor across firms, away from non-adopters, and toward adopters. Finally, we estimate TFP improvements that are causally related to the adoption of robots, and we reveal a complementarity between robot adoption and exporting. Using our structural TFP estimates, we document that most of the manufacturing productivity decline in Spain before the financial crisis in our sample can be attributed to non-adopters.

By focusing attention on heterogeneity in robot adoption within narrowly defined industries, our results provide novel evidence how robots can potentially affect industry heterogeneity. Importantly, we find strictly non-negative employment effects in robot adopters, even when focusing on specific skills or groups of workers. Indeed, negative employment effects materialize where they are ex-ante the least expected, namely in those firms that do not automate their production process.

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A Online Appendix

A.1 Details to data from the International Federation of Robotics (IFR)

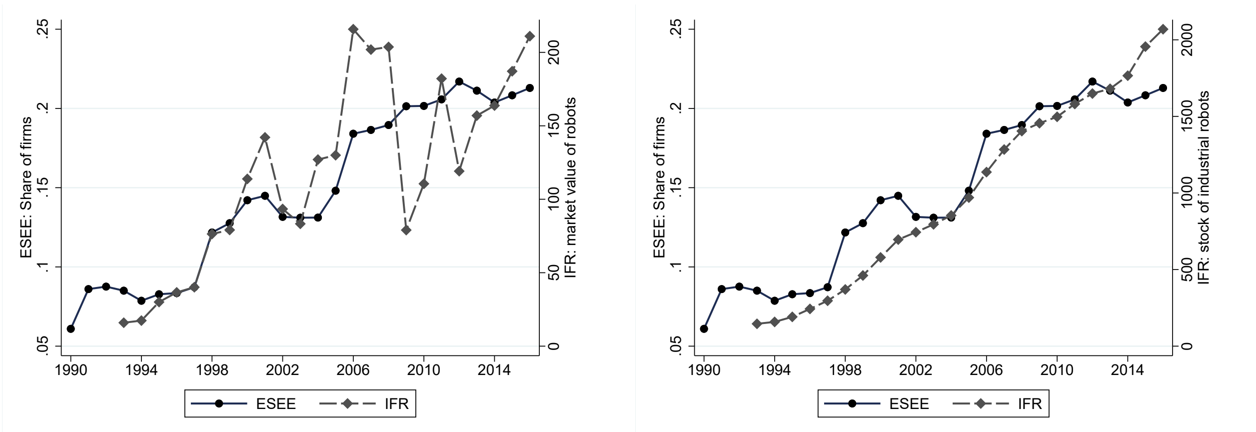
Table A.1: Sector mapping IFR to ESEE

Description SEPI website	Corresponding IFR industries
1. Meat products	10-12 - Food and beverages
2. Food and tobacco	10-12 - Food and beverages
3. Beverage	10-12 - Food and beverages
4. Textiles and clothing	13-15 - Textiles
5. Leather, fur and footwear	13-15 - Textiles
6. Timber	16 - Wood and furniture
7. Paper	17-18 - Paper
8. Printing	17-18 - Paper
9. Chemicals and pharmaceuticals	19 - Pharmaceuticals, cosmetics & 20-21 - other chemical products n.e.c. & 229 - Chemical products, unspecified
10. Plastic and rubber products	22 - Rubber and plastic products (non-automotive)
11. Nonmetal mineral products	23 - Glass, ceramics, stone, mineral products
12. Basic metal products	24 - Basic metals & 289 - Metal, unspecified
13. Fabricated metal products	25 - Metal products
14. Machinery and equipment	28 - Industrial machinery
15. Computer products, electronics and optical	275 - Household/domestic appliances & 262 - Computers and peripheral equipment & 263 - Info communication equipment, domestic and prof. & 265 - Medical, precision, optical instruments & 279 - Electrical/electronics unspecified
16. Electric materials and accessories	271 - Electrical machinery n.e.c. & 260 - Electronic components/devices & 261 - Semiconductors, LCD, LED
17. Vehicles and accessories	29 - Automotive
18. Other transport equipment	30 - Other vehicles
19. Furniture	16 - Wood and furniture
20. Other manufacturing	91 - All other manufacturing branches

Notes: This table shows our mapping of industries between the official classification in the ESEE data according to the SEPI website (left column) and the official sector definition in the IFR data (right column).

A.2 ESEE and IFR data: Time Series Comparisons

Figure A.1: Evolution of robot diffusion in Spain: Comparison of Data Sources



(a) Share of robot firms vs. market value of robots (b) Share of robot firms vs. stock of industrial robots

Notes: In both panels the solid black line depicts the share of firms using robots in their production process according to the full sample of firms in the ESEE data-set, while the dashed gray line depicts the market value of robots (left panel) or the stock of industrial robots (right panel) according to the IFR data.
Source: Authors' computations based on ESEE and IFR data.

A.3 Descriptive Statistics to Section 2

Table A.2: Timing of robot adoption across industries

	1991	1994	1998	2002	2006	2010	2014	Total
Motorized Vehicles	8	4	2	6	3	7	2	32
Furniture	5	1	4	4	1	2	4	21
Plastic & Rubber Products	8	7	6	2	7	4	7	41
Ferrous & Non-Ferrous Metals	1	2	3	3	2	5	0	16
Mineral Products (Non -Metal)	11	8	11	6	4	13	3	56
Other Transportation	4	3	3	3	2	2	1	18
Machinery & Electrical Equipments	8	7	5	2	2	4	3	31
Miscellaneous Manufacturing	3	4	1	2	1	1	2	14
Metal Products	13	7	7	11	9	20	10	77
Chemicals & Pharmaceuticals	7	7	7	7	1	11	10	50
Beverage	2	3	3	4	0	2	0	14
Paper Products	2	2	1	2	7	5	2	21
Industry & Agriculture Machinery	6	5	7	2	2	5	5	32
Food Products & Tobacco	9	12	14	6	4	12	13	70
Informatics, Electronics, Optics	2	3	3	2	1	1	1	13
Meat	5	3	3	2	5	7	3	28
Graphics Design	2	3	8	7	4	3	3	30
Textile & Wearing Apparel	4	8	9	7	9	8	2	47
Timber & Wooden Products	2	1	5	3	5	5	2	23
Leather & Footwear	1	0	4	1	3	1	0	10
Total	103	90	106	82	72	118	73	644

Notes: The table reports the number of firms that adopt robots across industries and years.

Table A.3: Descriptive statistics

	Robot adopters (1)	Non-adopters (2)	Observations (1)/(2)
Output (in logs)	16.164	14.873	7,483/24,402
	(1.766)	(1.648)	
Labor productivity (in logs)	10.552	10.316	7,381/24,027
	(0.650)	(0.674)	
Total employment (in logs)	4.474	3.511	7,500/24,595
	(1.368)	(1.188)	
Manufacturing employment (in logs)	4.421	3.463	7,360/24,155
	(1.344)	(1.164)	
Share of manufacturing employment	0.961	0.964	7,366/24,168
	(0.128)	(0.118)	
Share of production workers	0.699	0.705	2,420/9,418
	(0.183)	(0.197)	
# temporary workers (in logs)	2.754	1.981	5,713/16,410
	(1.445)	(1.343)	
# low-skilled workers (in logs)	4.409	3.509	2,370/9,271
	(1.316)	(1.122)	
# high-skilled workers (in logs)	1.567	0.859	2,370/9,271
	(1.352)	(1.102)	
Average wage (in logs)	10.136	9.968	7,419/24,204
	(0.447)	(0.488)	
Labor cost share	0.285	0.342	7,446/24,144
	(0.214)	(0.476)	
Capital stock (in logs)	15.297	13.714	7,130/23,266
	(1.973)	(1.994)	
Investments in machinery (in logs)	4.058	3.976	5,992/14,913
	(0.798)	(0.931)	
Capital intensity (in logs)	3.433	2.853	7,081/23,191
	(0.987)	(1.147)	
Skill intensity (in logs)	0.055	0.047	2,391/9,376
	(0.081)	(0.081)	
R&D intensity (in logs)	0.342	0.189	7,443/24,581
	(0.618)	(0.495)	
Exporter status	0.701	0.482	7,529/24,729
	(0.458)	(0.500)	
Importer status	0.686	0.467	7,529/24,729
	(0.464)	(0.499)	
Foreign owned	0.155	0.081	7,522/24,714
	(0.362)	(0.273)	
Assimilation of foreign technologies	0.169	0.083	2,221/8,630
	(0.375)	(0.276)	

Notes: The table reports means and standard deviations (in parentheses) of firm-specific variables for robot adopters (i.e. firms that start using robots at some point in time; column (1)) vs. non-adopters (i.e. firms that never use robots; column (2)). The numbers of observations reported in the final column correspond to the firm-year observations in columns (1) and (2). The sample spans the years 1990-2016 and is restricted to firms that do not use robots in the first year they enter the sample. Output is a firm's total production value. Labor productivity is value added per worker. Total employment is the average number of workers during the year. Manufacturing employment is the workforce employed at manufacturing as opposed to non-manufacturing establishments. Share of manufacturing employment is the number of workers employed at manufacturing establishments divided by the total number of workers employed by the firm. Share of production workers reports the share of workers in production jobs. Temporary workers are employees with temporary contracts. High-skilled workers are defined as workers with a five-year university degree, while low-skilled workers are all other workers. Average wage is computed as labor costs divided by the total number of workers. Labor cost share is labor costs divided by the total production value. Capital stock is the deflated capital stock for each firm. Investments in machinery include investments into installation of technical equipment and machinery tools. Capital intensity is the value of the firm's capital stock divided by effective work-hours. Skill intensity is the share of high-skilled workers. R&D intensity is the ratio of total expenses in R&D over total sales volume. We add one to all factor intensity variables as well as the number of high- and low-skilled workers before taking logs in order to keep zero observations. Exporter (importer) status is a dummy variable equal to one if the firm reports positive exports (imports). Foreign ownership indicates whether a firm is foreign owned by more than 50%. Assimilation of foreign technologies is a dummy variable indicating whether the firm assimilated foreign technologies.

A.4 Further descriptives

Table A.4: Descriptive statistics – Full Sample

	Full sample (1)	Observations (2)
Output (in logs)	15.509 (1.880)	40,123
Labor productivity (in logs)	10.437 (0.684)	39,561
Total employment (in logs)	3.979 (1.401)	40,421
Manufacturing employment (in logs)	3.925 (1.376)	39,642
Share of manufacturing employment	0.961 (0.123)	39,669
Share of production workers	0.702 0.190	15,159
# temporary workers (in logs)	2.369 (1.478)	28,492
# low-skilled workers (in logs)	3.924 (1.320)	14,878
# high-skilled workers (in logs)	1.215 (1.304)	14,878
Average wage (in logs)	10.064 (0.478)	39,894
Labor cost share	0.314 (0.394)	39,789
Capital stock (in logs)	14.492 (2.197)	38,290
Investments in machinery (in logs)	4.034 (0.853)	27,942
Capital intensity (in logs)	3.143 (1.139)	38,106
Skill intensity (in logs)	0.052 (0.081)	15,016
R&D intensity (in logs)	0.266 (0.554)	40,298
Exporter status	0.584 (0.493)	40,609
Importer status	0.567 (0.495)	40,609
Foreign owned	0.130 (0.337)	40,567
Assimilation of foreign technologies	0.125 (0.331)	13,799

Notes: The table reports means and standard deviations (in parentheses) of firm-specific variables for the full sample (i.e. robot adopters, non-adopters, and firms entered with robots; column (1)). The numbers of observations reported in column (2) correspond to the firm-year observations. The sample spans the years 1990-2016 and is restricted to firms that do not use robots in the first year they enter the sample. Output is a firm's total production value. Labor productivity is value added per worker. Total employment is the average number of workers during the year. Manufacturing employment is the workforce employed at manufacturing as opposed to non-manufacturing establishments. Share of manufacturing employment is the number of workers employed at manufacturing establishments divided by the total number of workers employed by the firm. Share of production workers reports the share of workers in production jobs. Temporary workers are employees with temporary contracts. High-skilled workers are defined as workers with a five-year university degree, while low-skilled workers are all other workers. Average wage is computed as labor costs divided by the total number of workers. Labor cost share is labor costs divided by the total production value. Capital stock is deflated for each firm. Investments in machinery include investments into installation of technical equipment and machinery tools. Capital intensity is the value of the firm's capital stock divided by effective work-hours. Skill intensity is the share of high-skilled workers. R&D intensity is the ratio of total expenses in R&D over total sales volume. We add one to all factor intensity variables as well as the number of high- and low-skilled workers before taking logs in order to keep zero observations. Exporter (importer) status is a dummy variable equal to one if the firm reports positive exports (imports). Foreign ownership indicates whether a firm is foreign owned by more than 50%. Assimilation of foreign technologies is a dummy variable indicating whether the firm assimilated foreign technologies.

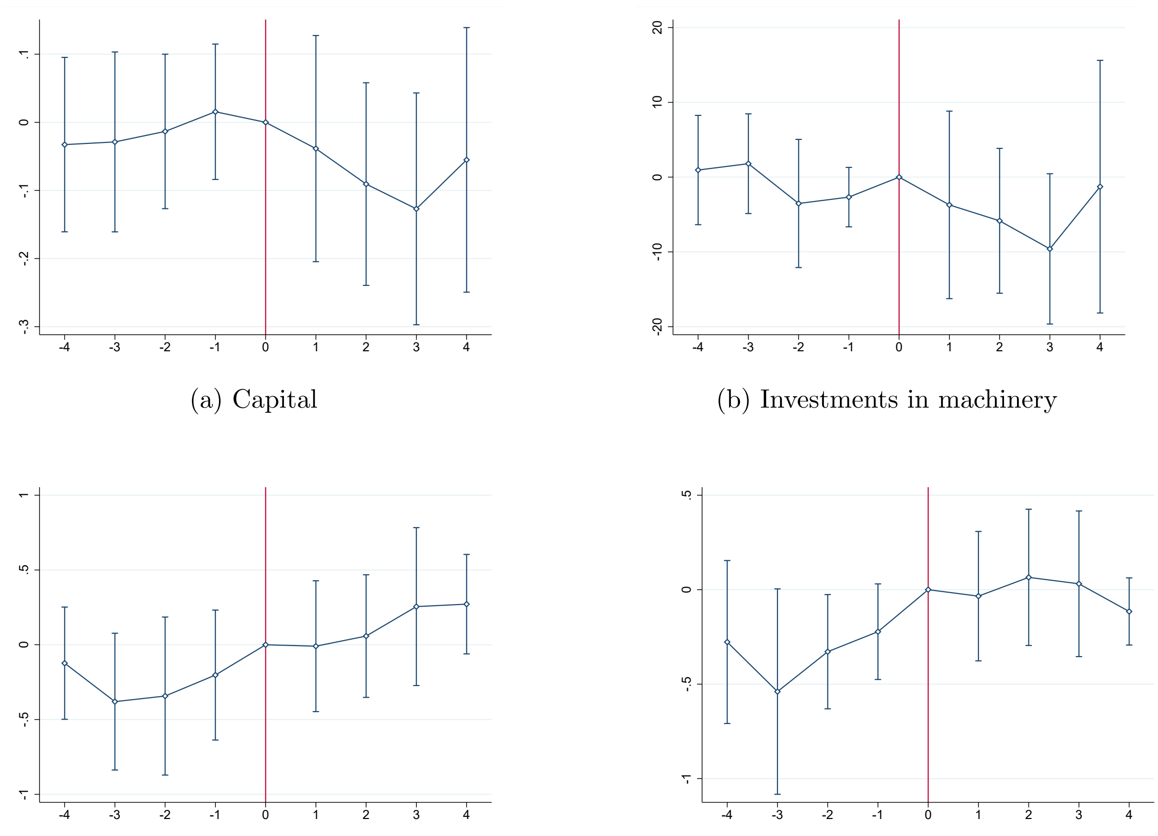
Table A.5: Descriptive statistics – Exports and robot adoption accross industries

Industry	Share of exporting firms	Share of firms using robots
Meat	.565	.159
Food Products & Tobacco	.473	.217
Beverage	.625	.311
Textile & Wearing Apparel	.525	.122
Leather & Footwear	.599	.059
Timber & Wooden Products	.426	.154
Paper Products	.65	.197
Graphics Design	.419	.103
Chemical & Pharmaceutical Products	.773	.197
Plastic & Rubber Products	.653	.34
Mineral Products (Non-Metal Products)	.467	.303
Ferrous Metals & Non-Ferrous Metals	.743	.296
Metal Products	.501	.251
Agricultural Machinery	.729	.228
Informatics, Electronics, Optics	.744	.366
Machinery & Electrical Equipment	.614	.323
Motorized Vehicles	.8	.524
Other Transportation Equipment	.695	.285
Furniture	.513	.197
Miscellaneous Manufacturing	.743	.185
Missing	.745	.343

Notes: The table reports the share of exporting firms and the share of firms using robots in their production process by industry.

A.5 Placebo event study analysis

Figure A.2: Placebo event study analysis: before-after effects



(a) Capital

(b) Investments in machinery

(c) Process innovations

(d) Innovations in terms of organizational methods

Notes: Points on the graph are the $\gamma_k, k \in -4, ..., 4$, coefficients in the estimating equation 1. The values of the dependent variable are normalized to zero in the year the firm adopts robots, so that $\gamma_0 = 0$. The underlying sample consists of 123 firms that are classified as placebo robot adopters over the sample period using propensity scores to assign the top 5% of non-adopters, which are most likely to adopt robots, into the group robot adopters. Vertical lines represent 90% confidence intervals.

A.6 Detailed derivations corresponding to Section 3

We use this section to provide analytical details corresponding to the results presented in Section 3 in the main text of the paper. We proceed as follows. First, we present the main model and its basic assumptions. Second, we discuss the main results of the basic model with one source of firm heterogeneity, viz. across-firm differences in $\phi(\omega)$ but no differences in the degree of complexity, $N(\omega) = N$. These results form the basis of our discussion in Section 3.3. Thirdly, we introduce the possibility of exporting and discuss its implications. This corresponds to Section 3.2.2. Finally, we allow for firm heterogeneity in $N(\omega)$ and consider two skill types of labor, low- and high-skilled workers. This is relevant for Section 3.2.3.

A.6.1 Basic set-up

Consider an industry in which a large number of monopolistically competitive firms produce horizontally differentiated goods. A firm ω is selling its unique variety at price $p(\omega)$ to consumers, facing an iso-elastic demand $q(\omega)$ of the form

$$q(\omega) = Ap(\omega)^{-\frac{1}{1-\beta}}, \tag{A.1}$$

where β controls the (constant) elasticity of substitution $1/(1-\beta) > 1$ between any two varieties, and A is a demand shifter.[52] As for the production side, we follow Acemoglu and Restrepo (2018*b*) in writing output as a composite of different tasks combined in a constant elasticity of substitution (CES) aggregate. However, we depart from Acemoglu and Restrepo (2018*b*) by introducing two types of firm heterogeneity into their framework. Specifically, we allow firms to differ in terms of their productivity (and thus size) and the complexity of tasks (and thus the likelihood of tasks being automated). The first type is the standard Melitz (2003) heterogeneity meaning that firms differ in their exogenous (baseline) productivity denoted by $\phi(\omega)$. We index tasks by i and assume that they can be ordered according to their complexity where a higher index i reflects higher complexity. Specifically, output of firm ω is given by

$$x(\omega) = \phi(\omega)\left(\int_{N(\omega)-1}^{N(\omega)} x(\omega, i)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}, \tag{A.2}$$

where σ denotes the elasticity of substitution between any two tasks and $x(\omega, i)$ is the output of task i in firm ω. The parameter $N(\omega)$ generates a second type of firm heterogeneity in the model. It is given exogenously and governs the set of tasks the firm has to perform, with the task range normalized to one and with the limits of integration given by $N(\omega) - 1$ and $N(\omega)$.[53] An increase in

[52] As is well known, the demand function in Eq. (A.1) with $A \equiv EP^{\frac{\beta}{1-\beta}}$ and $P = \left[\int_{\omega\in\Omega} p(\omega)^{\frac{-\beta}{1-\beta}} d\omega\right]^{-\frac{1-\beta}{\beta}}$ is implied by a standard utility maximization problem where consumers have a CES utility function $U = \left[\int_{\omega\in\Omega} q(\omega)^{\beta} d\omega\right]^{\frac{1}{\beta}}$ and face a budget constraint $E = \int_{\omega\in\Omega} p(\omega)q(\omega)d\omega$ with E being the total expenditure on the set of available varieties Ω.

[53] Capuano et al. (2020) provide evidence for substantial heterogeneity in the type of tasks performed by German plants even if they are operating in the same industry. Most of the results we derive in our theoretical analysis do

$N(\omega)$ reflects quality upgrading, in the sense that new and more complex tasks appear and replace old tasks in the production process (the least complex ones). Crucially, we assume that the simpler tasks with index numbers $i \leq I$ can be performed by robots or human labor, while the more complex tasks with index numbers $i > I$ are bound to be performed by human labor. The parameter I thus reflects the ability level of robots in performing complex tasks. This parameter is likely to vary across industries and through time as technology advances. Output at the task level is given by

$$x(\omega, i) = \mathbb{1}\left[i \leq I\right] \eta(i) k(\omega, i) + \gamma(i) l(\omega, i), \tag{A.3}$$

where $\mathbb{1}[i \leq I]$ is a 0/1 indicator equal to one if $i \leq I$ and zero otherwise, and $\gamma(i)$ and $\eta(i)$ denote, respectively, the productivity of labor l and robot capital k in task i.[54] Crucially, robot capital and labor are perfect substitutes for one another in all tasks $i \leq I$. This view highlights an important aspect of automation, namely that machines are used to substitute for human labor (Acemoglu and Restrepo, 2018*a*, p.2).

As in Acemoglu and Restrepo (2018*a*), we assume that the ratio of $\eta(i)/\gamma(i)$ is strictly decreasing in i, which formalizes a comparative advantage of labor in more complex tasks. Moreover, we assume that the effective robot capital costs (at rental rate r) are strictly below the effective labor costs (at wage rate w) for all automatable tasks. Formally, we have $r/\eta(I) < w/\gamma(I)$. These assumptions reflect the view that human labor is more valuable in performing complex tasks than robot capital. Accordingly, we can write the unit production costs of a firm using robots to perform all tasks $i \leq I$ as

$$c^a(\phi(\omega), N(\omega), I) = \frac{1}{\phi(\omega)} \left[\eta(N(\omega), I) r^{1-\sigma} + \gamma(N(\omega), I) w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \tag{A.4}$$

where $\eta(N(\omega), I) \equiv \left(\int_{N(\omega)-1}^{I} \eta(i)^{\sigma-1} di\right)^{\frac{1}{\sigma}}$ and $\gamma(N(\omega), I) \equiv \left(\int_{I}^{N(\omega)} \gamma(i)^{\sigma-1} di\right)^{\frac{1}{\sigma}}$ summarize the productivity over all tasks performed by robots and labor, respectively.[55] The superscript a indicates that the production process has been automated. However, this decision is endogenous and requires incurring a fixed cost, denoted by $F^a > 0$. Not paying the fixed cost means that the firm has to perform all tasks using human labor with corresponding unit cost of $c(\phi(\omega), N(\omega), N(\omega) - 1) =$

not depend on differences in $N(\omega)$. However, allowing for this heterogeneity in a simple extension of our model will generate differences in the skill intensity of firms that are consistent with our data, as will become evident below.

[54] Combining the specifications for output at the firm and task level according to Eq. A.2 and A.3, respectively, imply that firms only need capital if they use robots in the production process. To allow for non-robot capital in the production function one could adjust Eq. A.2 and write output of firm ω as $x(\omega) = \phi(\omega) x_k(\omega)^{\alpha_k} \left[\left(\int_{N(\omega)-1}^{N(\omega)} x(\omega, i)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}\right]^{\alpha_l}$, with $\alpha_k + \alpha_l = 1$ and $\alpha_k, \alpha_l > 0$, and $x_k(\omega)$ denoting tasks purely performed by capital (e.g. machines). We simplify the analysis throughout section 3 by setting $\alpha_k = 0$ and $\alpha_l = 1$ and thus, abstract from non-robot capital as an additional source of input here, since it does not affect the analysis on the selection and treatment effects, as long as firms do not differ in terms of the cost-share parameters α_k and α_l. However, in part 6, when we turn towards a TFP estimation, we explicitly allow for non-robot capital in the production function.

[55] As shown in Acemoglu and Restrepo (2018*b*), we can write output as $x(\omega) = [\eta(N(\omega), I) K(\omega)^{\rho} + \gamma(N(\omega), I) L(\omega)^{\rho}]^{\frac{1}{\rho}}$, with $\rho = (\sigma - 1)/\sigma$, where $\int_{N(\omega)-1}^{I} k(\omega, i) di = K(\omega)$ and $\int_{I}^{N(\omega)} l(\omega, i) di = L(\omega)$. The corresponding unit-cost function is thus given by (A.4).

$\frac{1}{\phi(\omega)}\left[\gamma(N(\omega),N(\omega)-1)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$.

Using constant mark-up pricing, we can write a firm's profit gain from robot adoption, defined as $\Delta\pi(\omega) \equiv \pi^a(\omega) - \pi(\omega)$, as follows:[56]

$$\Delta\pi(\omega) = (1-\beta)A\left\{\frac{1}{\beta}\frac{1}{\phi(\omega)}\left[\gamma\left(N(\omega),N(\omega)-1\right)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}\right\}^{-\frac{\beta}{1-\beta}}\left[\kappa\left(N(\omega),I\right)-1\right] - F^a, \quad \text{(A.5)}$$

where $\kappa(\cdot)$ is defined as

$$\kappa\left(N(\omega),I\right) \equiv \left(\frac{\left(\int_{N(\omega)-1}^{I}\eta(i)^{\sigma-1}di\right)^{1/\sigma} r^{1-\sigma} + \left(\int_{I}^{N(\omega)}\gamma(i)^{\sigma-1}di\right)^{1/\sigma} w^{1-\sigma}}{\left(\int_{N(\omega)-1}^{I}\gamma(i)^{\sigma-1}di\right)^{1/\sigma} w^{1-\sigma} + \left(\int_{I}^{N(\omega)}\gamma(i)^{\sigma-1}di\right)^{1/\sigma} w^{1-\sigma}}\right)^{\frac{1}{\sigma-1}\frac{\beta}{1-\beta}}. \quad \text{(A.6)}$$

This expression is (weakly) larger than one and reflects the marginal cost savings from robot adoption. Given that labor has a comparative advantage in performing more complex tasks and the fact that $r/\eta(I) < w/\gamma(I)$, we find that $\kappa(\cdot)$ is, ceteris paribus, increasing in the level of robot technology I and decreasing in the complexity of tasks $N(\omega)$. If firms face a highly complex production process such that $I = N(\omega) - 1$, then all tasks must be performed by labor and there are consequently no cost savings from robot adoption, $\kappa(N(\omega), N(\omega)-1) = 1$.[57]

A.6.2 The robot adoption decision

In the model, firms differ in their baseline productivity $\phi(\omega)$ and the complexity of their production process $N(\omega)$. In a first step, we focus on just one-dimensional heterogeneity by assuming that all firms have to perform the same set of tasks, given by $N(\omega) = N$. Hence, firms are fully described by their productivity ϕ and we can omit the firm index ω to save on notation. We can write firm profits for robot adopters and non-adopters, respectively, as

$$\pi(\phi) = (1-\beta)A\left\{\frac{1}{\beta}\left[\gamma(N,N-1)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}\right\}^{-\frac{\beta}{1-\beta}} - F \quad \text{and} \quad \text{(A.7)}$$

$$\pi^a(\phi) = (1-\beta)A\left\{\frac{1}{\beta}\left[\eta(N,I)r^{1-\sigma} + \gamma(N,I)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}\right\}^{-\frac{\beta}{1-\beta}} - F - F^a. \quad \text{(A.8)}$$

Given that robots have a comparative advantage in all tasks $i \leq I$, we know that $\left[\gamma(N,N-1)w^{1-\sigma}\right] < \left[\eta(N,I)r^{1-\sigma} + \gamma(N,I)w^{1-\sigma}\right]$. Without loss of generality, we normalize the left-hand side by set-

[56]Note that profits of firm ω using robots can be written as $\pi^a(\omega) = (1-\beta)A\left[\frac{1}{\beta}c^a(\phi(\omega),N(\omega),I)\right]^{-\frac{\beta}{1-\beta}} - F^a - F$ while profits for the same firm using human labor instead of robots are $\pi(\omega) = (1-\beta)A\left[\frac{1}{\beta}c(\phi(\omega),N(\omega),N(\omega)-1)\right]^{-\frac{\beta}{1-\beta}} - F$, where F denotes overall fixed costs of production. Computing the difference between the two gives Eq. (A.5).

[57]Clearly, from inspection of Eq. A.6 cost savings also depend on factor prices for labor and capital. While allowing firms to differ in terms of factor prices by introducing capital or labor market frictions is way beyond the scope of the theoretical framework, we control for such differences in the empirical exercise below.

ting $\left[\gamma(N, N-1) w^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = 1$ and we define $\left[\eta(N, I) r^{1-\sigma} + \gamma(N, I) w^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = 1/\bar{\eta}$ with $\bar{\eta} > 1$. Furthermore, we choose $F^a = (\alpha - 1)F$ with $\alpha > 1$. We can thus rewrite profits as

$$\pi(\phi) = (1-\beta) A \left(\frac{1}{\beta} \frac{1}{\phi}\right)^{-\frac{\beta}{1-\beta}} - F, \tag{A.9}$$

$$\pi^a(\phi) = (1-\beta) A \left(\frac{1}{\beta} \frac{1}{\phi \bar{\eta}}\right)^{-\frac{\beta}{1-\beta}} - \alpha F. \tag{A.10}$$

To determine the domestic cut-off productivity, denoted by ϕ^*, we can use $\pi(\phi^*) = 0$. The cut-off productivity for robot adoption ϕ^r can be determined by using the indifference condition $\pi(\phi^r) = \pi^a(\phi^r)$ along with $\pi(\phi^*) = 0$ to compute

$$\phi^r = \phi^* \left(\frac{\alpha - 1}{\bar{\eta}^{\frac{\beta}{1-\beta}} - 1}\right)^{\frac{1-\beta}{\beta}}. \tag{A.11}$$

Using these cut-off productivities, we can define the share of firms that use robots as

$$s_r \equiv \frac{1 - G(\phi^r)}{1 - G(\phi^*)}, \tag{A.12}$$

where $G(\cdot)$ denotes the cumulative distribution function of productivity. From inspection of Equation (A.11) we can conclude that a lower fixed cost for robot adoption or a higher share of automatable tasks (and thus $\bar{\eta}$) raises the share of robot adopters, i.e. $\partial s_r / \partial \alpha < 0$ and $\partial s_r / \partial I > 0$.

Discussing the implications for the composition of firms within industries requires to also specify the details on the entry (and exit) process of firms. As this is standard in the literature on heterogeneous firms, we refer the interested reader for details to Melitz (2003). Here, we briefly outline how the endogenous cut-off productivity ϕ^* can be determined. Specifically, it is determined by two conditions. The first condition uses the relation between the average profit per firm and the cut-off productivity level, the so-called zero-cutoff productivity. It can be computed as the average profits over all active firms, that is

$$\bar{\pi} = (1-\beta) A \left(\frac{1}{\beta} \frac{1}{\widetilde{\phi}}\right)^{-\frac{\beta}{1-\beta}} - F - F(\alpha - 1) \frac{1 - G(\phi^r)}{1 - G(\phi^*)}, \tag{A.13}$$

where $\bar{\pi}$ denotes the average profits over all active firms and $\widetilde{\phi}$ is the average (expected) productivity level, defined as

$$\widetilde{\phi} \equiv \left(\int_{\phi^*}^{\phi^r} \phi^{\frac{\beta}{1-\beta}} \frac{g(\phi)}{1 - G(\phi^*)} d\phi + \int_{\phi^r}^{\infty} (\eta \phi)^{\frac{\beta}{1-\beta}} \frac{g(\phi)}{1 - G(\phi^*)} d\phi\right)^{\frac{1-\beta}{\beta}}. \tag{A.14}$$

The second condition, called the free entry condition, requires that the net value of entry is zero, i.e. the sunk market entry costs (f_e) are equal to the expected profits (discounted by δ). Formally, this condition reads as:

$$\bar{\pi} = \frac{\delta f_e}{1 - G(\phi^*)}. \tag{A.15}$$

Both equations can be used to determine a unique cut-off productivity level and show that a lower fixed cost of robot adoption or a higher level of robot technology affects the composition of firms within industries. Following Melitz (2003), we know that ex-ante more productive firms gain market share by reducing marginal costs due to robot adoption. This raises the cut-off productivity at which firms are able to survive in the market. Put differently, increasing robot exposure raises the exit rate among non-robot firms and reduces their output and employment. This proves the results described in Section 3.3.

A.6.3 Exporting

When allowing for trade with a symmetric partner country, we can sort firms into four groups, namely combinations of robot adopters vs. non-adopters (indicating robot adopters by a superscript a) and exporters vs. non-exporters (indicated by subscripts x and d, respectively). Specifically, we can write firm profits for the different types as

$$\pi_d(\phi) = (1-\beta)A\left\{\frac{1}{\beta}\left[\gamma(N,N-1)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}\right\}^{-\frac{\beta}{1-\beta}} - F, \tag{A.16}$$

$$\pi_d^a(\phi) = (1-\beta)A\left\{\frac{1}{\beta}\left[\eta(N,I)r^{1-\sigma} + \gamma(N,I)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}\right\}^{-\frac{\beta}{1-\beta}} - F - F^a, \tag{A.17}$$

$$\pi_x(\phi) = \left(1+\tau^{-\frac{\beta}{1-\beta}}\right)(1-\beta)A\left\{\frac{1}{\beta}\left[\gamma(N,N-1)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}\right\}^{-\frac{\beta}{1-\beta}} - F - F^x, \tag{A.18}$$

$$\pi_x^a(\phi) = \left(1+\tau^{-\frac{\beta}{1-\beta}}\right)(1-\beta)A\left\{\frac{1}{\beta}\left[\eta(N,I)r^{1-\sigma} + \gamma(N,I)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}\right\}^{-\frac{\beta}{1-\beta}} - F - F^a - F^x. \tag{A.19}$$

Again, setting $\left[\gamma(N,N-1)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = 1$, defining $\left[\eta(N,I)r^{1-\sigma} + \gamma(N,I)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = 1/\bar{\eta}$ with $\bar{\eta} > 1$, and setting $F^a = (\alpha-1)F$, we can rewrite profits as

$$\pi_d(\phi) = (1-\beta)A\left(\frac{1}{\beta}\frac{1}{\phi}\right)^{-\frac{\beta}{1-\beta}} - F, \tag{A.20}$$

$$\pi_d^a(\phi) = (1-\beta)A\left(\frac{1}{\beta}\frac{1}{\phi\bar{\eta}}\right)^{-\frac{\beta}{1-\beta}} - \alpha F, \tag{A.21}$$

$$\pi_x(\phi) = \left(1+\tau^{-\frac{\beta}{1-\beta}}\right)(1-\beta)A\left(\frac{1}{\beta}\frac{1}{\phi}\right)^{-\frac{\beta}{1-\beta}} - F - F^x, \tag{A.22}$$

$$\pi_x^r(\phi) = \left(1+\tau^{-\frac{\beta}{1-\beta}}\right)(1-\beta)A\left(\frac{1}{\beta}\frac{1}{\phi\bar{\eta}}\right)^{-\frac{\beta}{1-\beta}} - \alpha F - F^x. \tag{A.23}$$

Except for different variable labels, this system is identical to the one described in Bustos (2011) (on page 310). We can thus build on her insights and follow the same steps. Accordingly, we focus on cost and parameter conditions that guarantee that the least productive firms serve only the domestic market and do not adopt robots, while more productive firms export and only the most productive exporters find it attractive to adopt robots. Importantly, the descriptive statistics obtained from our data and described in the main text reveal that the share of robot adopters is considerably lower than the share of exporting firms. It is therefore plausible to assume that the marginal exporter is a non-adopter, i.e., a firm that does not use robots. As shown in Bustos (2011), this is the case with a sufficiently high fixed cost of robot adoption relative to exporting. The exporter cut-off ϕ^x is determined by the indifference condition $\pi_d(\phi^x) = \pi_x(\phi^x)$. Combining this condition with $\pi_d(\phi^*) = 0$ entails

$$\phi^x = \phi^* \tau \left(\frac{F^x}{F} \right)^{\frac{1-\beta}{\beta}}. \tag{A.24}$$

To determine the cut-off productivity for robot adoption in the open economy ϕ^r, we use $\pi_x(\phi^r) = \pi_x^a(\phi^r)$. Using the zero cut-off profit condition for the least productive firm, this allows us to compute:

$$\phi^r = \phi^* \frac{1}{\left(1 + \tau^{-\frac{\beta}{1-\beta}}\right)^{\frac{\beta}{1-\beta}}} \left(\frac{\alpha - 1}{\bar{\eta}^{\frac{\beta}{1-\beta}} - 1} \right)^{\frac{1-\beta}{\beta}}. \tag{A.25}$$

Using Equation (A.25), we can conclude that a reduction in variable trade costs τ raises the share of robot adopters, i.e. $\partial s_r / \partial \tau < 0$. As discussed in detail in Bustos (2011), we know that the incentives for adopting robots are higher for exporting firms, as the gains from doing so—the reduction in variable production costs—can be scaled up to a larger customer base in home and foreign. This completes the discussion corresponding to Section 3.2.2.

A.6.4 Skill heterogeneity

In the main text we briefly discuss an extension with two types of workers, namely low-skilled and high-skilled workers, indexed by subscripts l and h, respectively. Accordingly, we have

$$x(\omega, i) = \mathbb{1}\left[i \leq I\right] \eta(i) k(\omega, i) + \gamma_l(i) l_l(\omega, i) + \gamma_h(i) l_h(\omega, i). \tag{A.26}$$

In such an environment, firms will not only compare the production costs of robots and human labor across tasks, but also consider the skill-specific effective labor costs in each task, i.e., the firm will benchmark $w_l/\gamma_l(i)$ against $w_h/\gamma_h(i)$. The task-level production function in (A.26) implies that low-skilled and high-skilled workers are substitutes in the performance of tasks. Following Acemoglu and Autor (2011), we impose a comparative advantage of high-skilled workers over their low-skilled coworkers that is increasing in the complexity of tasks. As discussed in detailed in Koch (2016), we can define a unique threshold task $z \in (0,1)$ for which the firm is exactly indifferent between hiring low-skilled and hiring high-skilled workers, at prevailing skill premium $s \equiv w_h/w_l$. Put differently, the unit costs of performing task z are the same irrespective of the assigned skill type $k = l, h$. This establishes

$$w_l/\gamma_l(z) = w_h/\gamma_h(z). \tag{A.27}$$

Koch (2016) discusses parameter constraints (on the comparative advantage schedule, factor endowments, etc.) within a general equilibrium framework that guarantee the existence of an interior solution, $z \in (N-1, N)$. Intuitively, we need a skill premium that exceeds the productivity advantage of high-skilled workers in some tasks. Under this constraint, we can establish that low-skilled workers will be assigned to all tasks $i < z$, while high-skilled workers will be assigned to all tasks $i \geq z$. Under the additional constraint that robots cannot automate all tasks performed by low-skilled workers, $I < z$, we obtain for the unit production costs

$$c^a(\phi, N, I) = \frac{1}{\phi}\left[\eta(N,I)r^{1-\sigma} + \gamma_l(I,z)w^{1-\sigma} + \gamma_h(N,z)w^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \tag{A.28}$$

where $\eta(N,I) \equiv \left(\int_{N-1}^{I}\eta(i)^{\sigma-1}di\right)^{\frac{1}{\sigma}}$, $\gamma_l(I,z) \equiv \left(\int_{I}^{z}\gamma_l(i)^{\sigma-1}di\right)^{\frac{1}{\sigma}}$ and $\gamma_h(N,z) \equiv \left(\int_{z}^{N}\gamma_h(i)^{\sigma-1}di\right)^{\frac{1}{\sigma}}$. In the main text, we use this extension with two skill types to conclude that firms with a higher skill intensity are less likely to adopt robots. Therefore, we now also consider heterogeneity of firms in the complexity of the production process, $N(\omega)$. For ease of exposition, we assume that some firms operate with a complexity equal to N, while others operate with $N^c > N$.[58] Suppose that $I > N^c - 1$, so that there is always some tasks that are automatable. Figure A.3 illustrates this situation. It is evident that more complex firms have (i) a higher share of tasks that are performed by high-skilled workers and (ii) that in these firms only a smaller fraction of tasks can be performed by robots. It follows that firms with a lower skill intensity are more likely to adopt robots. This completes the discussion corresponding to Section 3.2.3.[59]

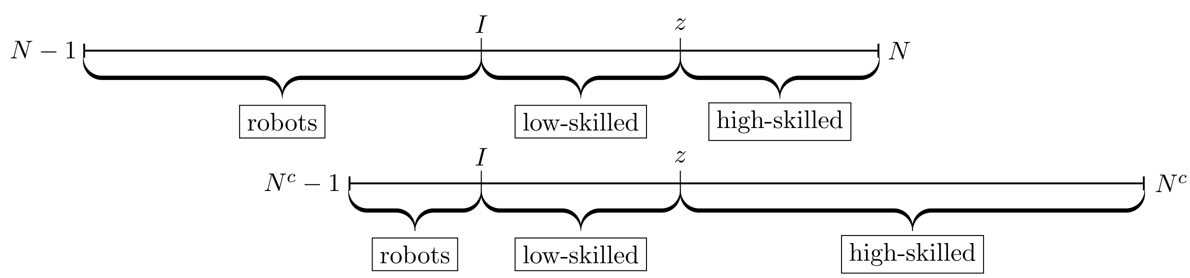
The task-output specified in A.26 can be in principle extended to additional allow for a skill-bias in the adoption of robots. To do so one could allow the efficiency parameter of high-skilled

[58] Different studies in the field of international economics have extended the Melitz (2003) framework to allow for heterogeneity in more than one dimension. Prominent examples include Davis and Harrigan (2011), Eaton et al. (2011), Hallak and Sivadasan (2013), Armenter and Koren (2015), Harrigan and Reshef (2015), and Helpman et al. (2017). For instance, Harrigan and Reshef (2015) also consider two types of labor with firms differing in both the baseline productivity φ and the Cobb-Douglas share parameter α which governs the skill intensity of the firm. They characterize firms by their "competitiveness", determined by both φ and α, and they apply the theory of copulas from mathematical statistics to determine the distribution of firms' competitiveness allowing for flexible correlations between φ and α. Another example is Capuano et al. (2020), who allow for two-dimensional heterogeneity in the context of offshoring. In their framework, firms differ in the range of tasks to be performed as well as the share of offshorable tasks.

[59] Of course, we could allow firms to hire multiple skills for the performance of tasks. One tractable way is by introducing a third group of medium-skilled workers, similar to the approach in Acemoglu and Autor (2011). In such a setting task output reads $x(\omega,i) = \mathbb{1}\left[i \leq I\right]\eta(i)k(\omega,i) + \gamma_l(i)l_l(\omega,i) + \gamma_m(i)l_m(\omega,i) + \gamma_h(i)l_h(\omega,i)$, where lower-script m denotes medium-skilled workers. However, since we are only able to distinguish between two types of workers in our data-set, we restrict the attention two low- and high-skilled workers.

workers to depend on the type of technology, such that is higher for firms that adopted robots. In such a setting robot adoption raises the comparative advantage of high-skilled relative to low-skilled workers in the performance of complex tasks. Hence, firms will hire more high-skilled workers and assign them to a broader range of task after the adoption of robots in the production process. While the decision to adopt robots is monotonic in the complexity of tasks in the current version, things are different when introducing a skill-bias of technological change. Even if firms might only have a small share of automatable tasks (and thus a high share of high-skilled workers) the skill-bias of robot adoption might still incentivize firms to do so. However, as long as the skill-bias is sufficiently small, this mechanism would not affect the selection analysis but would favor the hiring of high-skilled over low-skilled workers after the adoption of robots. Yet, another alternative to introduce a skill bias of robots is to explicitly allow robots to create new (more complex) tasks, that replace (or upgrade) the lowest-index tasks (see Acemoglu and Restrepo, 2018*b*). Again, this would favor the hiring of high-skilled relative to low-skilled workers after the adoption of robots. However, as our empirical analysis in section 5 has not revealed a skill bias after the adoption of robots, we stick to the simple version here.

Figure A.3: Skill allocation and automatable tasks for different complexities of the production process



A.7 Further results on robot adoption

Table A.6: Selection into robot adoption: Probit cross-sectional specification

	Robot adoption (0/1 indicator)						
Base year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output	0.170***	0.197***	0.144***	0.169***	0.180***	0.189***	0.296***
	(0.0236)	(0.0277)	(0.0281)	(0.0312)	(0.0334)	(0.0345)	(0.0544)
Labor productivity					-0.0442	-0.00446	0.119
					(0.0579)	(0.0627)	(0.109)
Skill intensity		-2.270**		-2.230**	-2.548**	-2.473**	-2.240*
		(0.925)		(0.976)	(1.044)	(1.048)	(1.324)
Share of manu-facturing workers		1.202*		1.165*	1.144*	1.127*	2.205
		(0.614)		(0.653)	(0.659)	(0.666)	(1.360)
Share of production workers		0.193		0.169	0.168	0.148	0.0561
		(0.125)		(0.129)	(0.131)	(0.131)	(0.199)
Exporter			0.175**	0.159**	0.161**	0.166**	0.411***
			(0.0761)	(0.0788)	(0.0793)	(0.0793)	(0.136)
Assimilation of foreign technologies			0.154*	0.0921	0.0825	0.0803	-0.119
			(0.0895)	(0.0943)	(0.0951)	(0.0953)	(0.185)
Importer			0.0476	0.0875	0.0684	0.0583	0.0703
			(0.0785)	(0.0809)	(0.0815)	(0.0815)	(0.141)
Foreign owned			-0.164	-0.171	-0.192*	-0.189	-0.404*
			(0.108)	(0.113)	(0.115)	(0.116)	(0.213)
Capital intensity	0.0855**	0.0787**	0.0856**	0.0827**	0.0852**	0.0921**	0.0902
	(0.0335)	(0.0355)	(0.0346)	(0.0366)	(0.0376)	(0.0384)	(0.0673)
R&D intensity	0.116	0.182**	0.0561	0.130	0.135	0.131	-0.0974
	(0.0758)	(0.0816)	(0.0813)	(0.0877)	(0.0876)	(0.0878)	(0.146)
Average wage						-0.180	-0.655***
						(0.115)	(0.225)
Interest rate							-0.004
							(0.0240)
Observations	2769	2648	2666	2550	2515	2500	1015
Pseudo R-squared	0.114	0.124	0.120	0.127	0.127	0.126	0.187

Notes: The dependent variable in all columns is a 0/1 indicator variable equal to one if the firm adopts robots during our sample period and zero otherwise. Output is the firm's deflated output value (in logs). Labor productivity is the firm's deflated value added per worker (in logs). Skill intensity is the firm's share of workers with a five-year university degree (in logs). Share manufacturing is the firm's share of manufacturing workers (in logs). Share production is the firm's share of production workers (in logs). Exporter is a dummy variable for positive exports. Assimilation of foreign technologies is a dummy variable indicating whether the firm assimilated foreign technologies. Importer is a dummy variable for positive imports. Foreign owned is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Capital intensity is defined as the firm's deflated capital stock per worker (in logs). R&D intensity is defined as the firm's deflated R&D expenditures relative to its deflated total sales (in logs). Average wage is defined as the firm's labor costs divided by the total number of workers (in logs). Interest rate is defined as the firm's interest rate on short-term dept (in percent). All estimates include industry-base-year fixed effects. We add one to all factor intensity variables before taking logs in order to keep zero observations. Therefore, all estimates include dummy variables (not reported) equal to one whenever the respective factor intensity variable is equal to zero before adding one. All explanatory variables are measured in the base year defined as the first year the firm appears in the sample. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.7: Robot adoption based on output quartiles: Linear cross-sectional specification

	Robot adoption (0/1 indicator)						
Base year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output 2nd quartile	0.0211	0.0228	0.0138	0.0160	0.0218	0.0227	0.0254
	(0.0151)	(0.0160)	(0.0153)	(0.0161)	(0.0169)	(0.0173)	(0.0214)
Output 3rd quartile	0.0549***	0.0635***	0.0425**	0.0504***	0.0552***	0.0577***	0.0887***
	(0.0168)	(0.0185)	(0.0179)	(0.0193)	(0.0201)	(0.0207)	(0.0284)
Output 4th quartile	0.138***	0.152***	0.115***	0.130***	0.139***	0.143***	0.152***
	(0.0217)	(0.0241)	(0.0245)	(0.0265)	(0.0276)	(0.0285)	(0.0367)
Labor productivity					-0.00713	-0.00170	0.0197
					(0.0114)	(0.0122)	(0.0177)
Skill intensity		-0.310**		-0.319**	-0.353***	-0.345***	-0.207
		(0.125)		(0.130)	(0.130)	(0.131)	(0.148)
Share of manu- facturing workers		0.220*		0.222*	0.219*	0.218*	0.237*
		(0.114)		(0.120)	(0.121)	(0.121)	(0.138)
Share of production workers		0.0429*		0.0394	0.0404	0.0381	0.0259
		(0.0238)		(0.0246)	(0.0249)	(0.0250)	(0.0322)
Exporter			0.0326**	0.0317*	0.0330**	0.0341**	0.0561***
			(0.0158)	(0.0163)	(0.0164)	(0.0164)	(0.0212)
Assimilation of foreign technologies			0.0494**	0.0346	0.0327	0.0325	-0.00142
			(0.0237)	(0.0243)	(0.0245)	(0.0245)	(0.0374)
Importer			0.00820	0.0156	0.0128	0.0114	0.00734
			(0.0157)	(0.0165)	(0.0166)	(0.0166)	(0.0232)
Foreign owned			-0.0291	-0.0343	-0.0392	-0.0394	-0.0586
			(0.0292)	(0.0299)	(0.0302)	(0.0304)	(0.0426)
Capital intensity	0.0199***	0.0187***	0.0182***	0.0174**	0.0177**	0.0187***	0.0132
	(0.00639)	(0.00677)	(0.00648)	(0.00687)	(0.00703)	(0.00715)	(0.00889)
R&D intensity	0.0166	0.0264	0.00311	0.0150	0.0156	0.0150	-0.0243
	(0.0196)	(0.0204)	(0.0201)	(0.0208)	(0.0213)	(0.0214)	(0.0242)
Average wage						-0.0247	-0.0781**
						(0.0227)	(0.0334)
Interest rate							0.001
							(0.00371)
Observations	3551	3374	3440	3268	3230	3213	1504
R-squared	0.151	0.156	0.151	0.154	0.158	0.158	0.203

Notes: The dependent variable in all columns is a 0/1 indicator variable equal to one if the firm adopts robots during our sample period and zero otherwise. The regressions include a full set of dummy variables indicating the firm's (quartile) position in the output distribution of the industry in which it is active. Labor productivity is the firm's deflated value added per worker (in logs). Skill intensity is the firm's share of workers with a five-year university degree (in logs). Share manufacturing is the firm's share of manufacturing workers (in logs). Share production is the firm's share of production workers (in logs). Exporter is a dummy variable for positive exports. Assimilation of foreign technologies is a dummy variable indicating whether the firm assimilated foreign technologies. Importer is a dummy variable for positive imports. Foreign owned is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Capital intensity is defined as the firm's deflated capital stock per worker (in logs). R&D intensity is defined as the firm's deflated R&D expenditures relative to its deflated total sales (in logs). Average wage is defined as the firm's labor costs divided by the total number of workers (in logs). Interest rate is defined as the firm's interest rate on short-term dept (in percent). All estimates include industry-base-year fixed effects. We add one to all factor intensity variables before taking logs in order to keep zero observations. Therefore, all estimates include dummy variables (not reported) equal to one whenever the respective factor intensity variable is equal to zero before adding one. All explanatory variables are measured in the base year defined as the first year the firm appears in the sample. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.8: Selection into robot adoption: Panel specification

	Robot adoption (0/1 indicator)						
Lagged	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output	0.0256***	0.0278***	0.0255***	0.0265***	0.0283***	0.0294***	0.0359***
	(0.00264)	(0.00296)	(0.00317)	(0.00336)	(0.00360)	(0.00367)	(0.00547)
Labor productivity					-0.0113**	-0.00714	-0.0120
					(0.00573)	(0.00633)	(0.0102)
Skill intensity		-0.102		-0.0960	-0.105	-0.103	-0.194*
		(0.0792)		(0.0845)	(0.0810)	(0.0811)	(0.105)
Share of manu-facturing workers		0.0575		0.0594	0.0586	0.0600	-0.0130
		(0.0450)		(0.0448)	(0.0448)	(0.0448)	(0.0986)
Share of production workers		0.0237**		0.0239**	0.0218*	0.0189	0.0230
		(0.0116)		(0.0119)	(0.0120)	(0.0122)	(0.0167)
Exporter			0.00313	0.00210	0.00314	0.00312	0.0194*
			(0.00776)	(0.00769)	(0.00772)	(0.00774)	(0.0111)
Importer			-0.00399	-0.000930	-0.00155	-0.00209	-0.00728
			(0.00815)	(0.00823)	(0.00823)	(0.00824)	(0.0120)
Foreign owned			-0.00780	-0.00235	-0.00498	-0.00293	0.00966
			(0.0154)	(0.0157)	(0.0156)	(0.0157)	(0.0262)
Assimilation of foreign technologies			0.0173	0.0197	0.0174	0.0174	0.00458
			(0.0129)	(0.0131)	(0.0131)	(0.0132)	(0.0223)
Capital intensity	0.00652*	0.00619*	0.00549	0.00496	0.00683*	0.00772**	0.0107**
	(0.00341)	(0.00342)	(0.00344)	(0.00345)	(0.00349)	(0.00355)	(0.00524)
R&D intensity	0.00203	0.00773	0.000835	0.00568	0.00390	0.00413	-0.00952
	(0.0114)	(0.0118)	(0.0116)	(0.0120)	(0.0121)	(0.0121)	(0.0176)
Average wage						-0.0189*	-0.0192
						(0.0112)	(0.0188)
Interest rate							-0.0015
							(0.0019)
Observations	6861	6760	6696	6599	6548	6523	3494
R-squared	0.067	0.068	0.068	0.068	0.069	0.069	0.077

Notes: The dependent variable in all columns is a 0/1 indicator variable equal to one if the firm adopts robots during our sample period and zero otherwise. Output is the firm's deflated output value (in logs). Labor productivity is the firm's deflated value added per worker (in logs). Skill intensity is the firm's share of workers with a five-year university degree (in logs). Share manufacturing is the firm's share of manufacturing workers (in logs). Share production is the firm's share of production workers (in logs). Exporter is a dummy variable for positive exports. Assimilation of foreign technologies is a dummy variable indicating whether the firm assimilated foreign technologies. Importer is a dummy variable for positive imports. Foreign owned is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Capital intensity is defined as the firm's deflated capital stock per worker (in logs). R&D intensity is defined as the firm's deflated R&D expenditures relative to its deflated total sales (in logs). Average wage is defined as the firm's labor costs divided by the total number of workers (in logs). Interest rate is defined as the firm's interest rate on short-term dept (in percent). All estimates include industry-base-year fixed effects. We add one to all factor intensity variables before taking logs in order to keep zero observations. Therefore, all estimates include dummy variables (not reported) equal to one whenever the respective factor intensity variable is equal to zero before adding one. All explanatory variables are measured in the base year defined as the first year the firm appears in the sample. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.9: Selection into robot adoption: Cross-sectional specification incl. temp workers

	Robot adoption (0/1 indicator)						
Base year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of temporary workers	0.00934	0.00760	0.00694	0.00523	0.00627	0.00579	0.00399
	(0.00858)	(0.00873)	(0.00872)	(0.00886)	(0.00894)	(0.00936)	(0.0146)
Output	0.0362***	0.0409***	0.0300***	0.0346***	0.0392***	0.0404***	0.0448***
	(0.00656)	(0.00729)	(0.00604)	(0.00811)	(0.00868)	(0.00916)	(0.0137)
Labor productivity					-0.0192	-0.0166	-0.00191
					(0.0142)	(0.0149)	(0.0265)
Skill intensity		-0.324*		-0.301*	-0.356**	-0.352**	-0.265
		(0.166)		(0.167)	(0.166)	(0.166)	(0.194)
Share of manufacturing workers		0.280**		0.281**	0.281**	0.281**	0.350**
		(0.131)		(0.137)	(0.139)	(0.139)	(0.159)
Share of production workers		0.0479		0.0399	0.0379	0.0359	0.0268
		(0.0311)		(0.0322)	(0.0327)	(0.0326)	(0.0453)
Exporter			0.0319**	0.0360*	0.0375*	0.0385*	0.0658**
			(0.0158)	(0.0208)	(0.0209)	(0.0210)	(0.0322)
Assimilation of foreign technologies			0.0467**	0.0401	0.0348	0.0349	-0.00318
			(0.0237)	(0.0301)	(0.0304)	(0.0304)	(0.0545)
Importer			0.00494	0.0168	0.0141	0.0116	-0.00817
			(0.0157)	(0.0205)	(0.0207)	(0.0208)	(0.0327)
Foreign owned			-0.0292	-0.0770**	-0.0803**	-0.0828**	-0.0684
			(0.0292)	(0.0341)	(0.0347)	(0.0349)	(0.0538)
Capital intensity	0.0246***	0.0227**	0.0166**	0.0222**	0.0235**	0.0237**	0.0205
	(0.00855)	(0.00901)	(0.00653)	(0.00916)	(0.00939)	(0.00951)	(0.0134)
R&D intensity	0.0130	0.0275	0.00309	0.0141	0.0155	0.0149	-0.0280
	(0.0235)	(0.0247)	(0.0200)	(0.0254)	(0.0266)	(0.0266)	(0.0331)
Average wage						-0.0138	-0.0645
						(0.0293)	(0.0462)
Interest rate							0.000898
							(0.00539)
Observations	2520	2453	2434	2369	2337	2325	973
R-squared	0.167	0.175	0.166	0.174	0.177	0.177	0.250

Notes: The dependent variable in all columns is a 0/1 indicator variable equal to one if the firm adopts robots during our sample period and zero otherwise. Share of temporary workers in the number of temporary workers over total employment (in logs). Output is the firm's deflated output value (in logs). Labor productivity is the firm's deflated value added per worker (in logs). Skill intensity is the firm's share of workers with a five-year university degree (in logs). Share manufacturing is the firm's share of manufacturing workers (in logs). Share production is the firm's share of production workers (in logs). Exporter is a dummy variable for positive exports. Assimilation of foreign technologies is a dummy variable indicating whether the firm assimilated foreign technologies. Importer is a dummy variable for positive imports. Foreign owned is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Capital intensity is defined as the firm's deflated capital stock per worker (in logs). R&D intensity is defined as the firm's deflated R&D expenditures relative to its deflated total sales (in logs). Average wage is defined as the firm's labor costs divided by the total number of workers (in logs). Interest rate is defined as the firm's interest rate on short-term dept (in percent). All estimates include industry-base-year fixed effects. We add one to all factor intensity variables before taking logs in order to keep zero observations. Therefore, all estimates include dummy variables (not reported) equal to one whenever the respective factor intensity variable is equal to zero before adding one. All explanatory variables are measured in the base year defined as the first year the firm appears in the sample. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.8 The decision to stop using robots

Here we investigate if firms that stop using robots are different to firms using robots continuously and what could potentially explain the decision to stop using robots. Table A.10 report means and standard deviations (in parentheses) of firm-specific variables for continuing firms (i.e. firms that start using robots at some point in time and do not switch afterwards; column (1)) vs. stoppers (i.e. firms that used robots before but stopped doing so at some point in time; column (2)). Table A.11 investigates the selection out of robot adoption by following a similar strategy to the one in Section 4.

Table A.10: Descriptive statistics

	Continuing (1)	Stoppers (2)	Observations (1)/(2)
Output (in logs)	16.722	16.172	9,089/6,191
	(1.744)	(1.804)	
Labor productivity (in logs)	10.661	10.567	8,981/6,117
	(0.627)	(0.694)	
Total employment (in logs)	4.878	4.459	9,188/6,197
	(1.398)	(1.366)	
Manufacturing employment (in logs)	4.823	4.398	8,970/6,082
	(1.376)	(1.331)	
Share of manufacturing employment	0.955	0.959	8,977/6,089
	(0.130)	(0.133)	
# temporary workers (in logs)	3.020	2.709	7,168/4,606
	(1.481)	(1.486)	
# low-skilled workers (in logs)	4.751	4.379	3,438/2,038
	(1.333)	(1.314)	
# high-skilled workers (in logs)	1.955	1.559	3,438/2,038
	(1.395)	(1.362)	
Average wage (in logs)	10.239	10.173	9,095/6,157
	(0.412)	(0.434)	
Labor cost share	0.263	0.286	9,035/6,171
	(0.170)	(0.221)	
Capital stock (in logs)	15.921	15.368	8,666/5,940
	(1.869)	(1.997)	
Investments in machinery (in logs)	4.140	4.037	7,764/4,901
	(0.688)	(0.833)	
Capital intensity (in logs)	3.646	3.508	8,592/5,910
	(0.931)	(1.011)	
Skill intensity (in logs)	0.065	0.057	3,459/2,049
	(0.082)	(0.079)	
R&D intensity (in logs)	0.439	0.312	9,115/6,162
	(0.643)	(0.572)	
Exporter status	0.778	0.695	9,224/6,214
	(0.415)	(0.461)	
Importer status	0.758	0.683	9,224/6,214
	(0.428)	(0.465)	
Foreign owned	0.236	0.168	9,210/6,201
	(0.424)	(0.374)	
Share of production workers	69.305	70.197	3,521/2,087
	(17.617)	(18.446)	
Assimilation of foreign technologies	0.218	0.157	3,143/1,904
	(0.413)	(0.363)	

Notes: The table reports means and standard deviations (in parentheses) of firm-specific variables for continuing firms (i.e. firms that start using robots at some point in time and do not switch afterwards; column (1)) vs. stoppers (i.e. firms that used robots before but stopped doing so at some point in time; column (2)). The numbers of observations reported in the final column correspond to the firm-year observations in columns (1) and (2). The sample spans the years 1990-2016 and is restricted to firms that do not use robots in the first year they enter the sample. Output is a firm's total production value. Labor productivity is value added per worker. Total employment is the average number of workers during the year. Manufacturing employment is the workforce employed at manufacturing as opposed to non-manufacturing establishments. Share of manufacturing employment is the number of workers employed at manufacturing establishments divided by the total number of workers employed by the firm. Temporary workers are employees with temporary contracts. High-skilled workers are defined as workers with a five-year university degree, while low-skilled workers are all other workers. Average wage is computed as labor costs divided by the total number of workers. Labor cost share is labor costs divided by the total production value. Capital stock is deflated for each firm. Investments in machinery include investments into installation of technical equipment and machinery tools. Capital intensity is the value of the firm's capital stock divided by effective work-hours. Skill intensity is the share of high-skilled workers. R&D intensity is the ratio of total expenses in R&D over total sales volume. We add one to all factor intensity variables as well as the number of high- and low-skilled workers before taking logs in order to keep zero observations. Exporter (importer) status is a dummy variable equal to one if the firm reports positive exports (imports). Foreign ownership indicates whether a firm is foreign owned by more than 50%. Assimilation of foreign technologies is a dummy variable indicating whether the firm assimilated foreign technologies.

Table A.11: Selection out of robot adoption: Cross-sectional specification

	Stoppers (0/1 indicator)						
Base year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output	-0.0308***	-0.0307**	-0.0313***	-0.0298**	-0.0286**	-0.0310**	-0.0259
	(0.0104)	(0.0120)	(0.0117)	(0.0130)	(0.0139)	(0.0145)	(0.0179)
Labor productivity					-0.00539	-0.0107	-0.0375
					(0.0282)	(0.0302)	(0.0373)
Skill intensity		0.417		0.336	0.412	0.395	0.337
		(0.283)		(0.291)	(0.297)	(0.299)	(0.345)
Share of manu-facturing workers		0.121		0.219	0.214	0.210	0.0599
		(0.196)		(0.197)	(0.196)	(0.197)	(0.312)
Share of production workers		-0.0153		-0.00610	-0.00649	-0.00223	-0.0425
		(0.0466)		(0.0484)	(0.0486)	(0.0488)	(0.0554)
Exporter			0.00379	-0.00476	0.000390	-0.00157	-0.0349
			(0.0358)	(0.0383)	(0.0386)	(0.0387)	(0.0488)
Assimilation of foreign technologies			-0.0620*	-0.0586*	-0.0545	-0.0534	-0.0307
			(0.0331)	(0.0344)	(0.0347)	(0.0349)	(0.0473)
Importer			0.0234	0.0240	0.0196	0.0195	0.0570
			(0.0344)	(0.0368)	(0.0371)	(0.0372)	(0.0450)
Foreign owned			-0.00744	-0.00854	-0.0112	-0.00952	0.0462
			(0.0384)	(0.0393)	(0.0396)	(0.0400)	(0.0540)
Capital intensity	-0.0116	-0.0118	-0.00794	-0.00666	-0.00908	-0.0113	0.00125
	(0.0159)	(0.0173)	(0.0166)	(0.0179)	(0.0188)	(0.0190)	(0.0264)
R&D intensity	-0.0384	-0.0388	-0.0371	-0.0340	-0.0526	-0.0538	-0.0529
	(0.0316)	(0.0332)	(0.0330)	(0.0345)	(0.0334)	(0.0338)	(0.0397)
Average wage						0.0296	0.0607
						(0.0553)	(0.0718)
Interest rate							0.000346
							(0.00877)
Observations	1534	1448	1453	1374	1363	1359	775
R^2	0.250	0.252	0.256	0.258	0.260	0.261	0.270

Notes: The dependent variable in all columns is a 0/1 indicator variable equal to one if the firm stops using robots during our sample period and zero if the firm started using robots and never stopped. Output is the firm's deflated output value (in logs). Labor productivity is the firm's deflated value added per worker (in logs). Skill intensity is the firm's share of workers with a five-year university degree (in logs). Share manufacturing is the firm's share of manufacturing workers (in logs). Share production is the firm's share of production workers (in logs). Exporter is a dummy variable for positive exports. Assimilation of foreign technologies is a dummy variable indicating whether the firm assimilated foreign technologies. Importer is a dummy variable for positive imports. Foreign owned is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Capital intensity is defined as the firm's deflated capital stock per worker (in logs). R&D intensity is defined as the firm's deflated R&D expenditures relative to its deflated total sales (in logs). Average wage is defined as the firm's labor costs divided by the total number of workers (in logs). Interest rate is defined as the firm's interest rate on short-term dept (in percent). All estimates include industry-base-year fixed effects. We add one to all factor intensity variables before taking logs in order to keep zero observations. Therefore, all estimates include dummy variables (not reported) equal to one whenever the respective factor intensity variable is equal to zero before adding one. All explanatory variables are measured in the base year defined as the first year the firm appears in the sample. The sample is restricted to firms that reported using robots at any point in time. Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.9 Propensity score estimates

In column (1) of Table A.12 we present multivariate probit regressions where we regress the robot indicator variable on a set of lagged variables we use in the propensity score estimation. In column (2) we present the univariate probit regression using the same variables. To construct the table we pool across all industries, while for the results shown in the paper, we estimate the propensity score by industry. All regressions include industry dummies.

Table A.12: Propensity scores estimation equation (probit specification)

	Robots multivariate	Robots univariate
	(1)	(2)
Sales	0.284***	0.304***
	(0.0311)	(0.0209)
Sales growth	-0.0145	0.221**
	(0.126)	(0.101)
Labor productivity	-0.114*	0.361***
	(0.0684)	(0.0545)
Labor productivity growth	0.0226	-0.0144
	(0.0664)	(0.0458)
Capital intensity	0.127***	0.320***
	(0.0381)	(0.0323)
Skill intensity	-1.806***	1.014**
	(0.649)	(0.459)
R&D intensity	0.165***	0.359***
	(0.0613)	(0.0556)
Exporter status	0.0567	0.554***
	(0.0780)	(0.0615)
Importer status	0.0331	0.579***
	(0.0803)	(0.0619)
Foreign ownership status	-0.0529	0.475***
	(0.109)	(0.0984)
Observations	4053	4053
Pseudo R-squared	0.157	

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.10 Further results on the effects of robot adoption

Table A.13: Labor market effects of robot adoption – the role of exports: Selection control

	Employment	Labor cost share	Low-skilled	High-skilled	Manufacturing employment	Share of manuf. employment	Average wage
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)
Robots_t	0.0523	-0.0436**	0.0214	0.130**	0.0258	-0.00520	-0.0148
	(0.0404)	(0.0175)	(0.0439)	(0.0547)	(0.0530)	(0.0125)	(0.0196)
Robots_{t-4}	0.0142	0.00152	-0.0138	0.0311	0.00788	-0.00168	-0.0183
	(0.0411)	(0.0226)	(0.0425)	(0.0580)	(0.0477)	(0.0105)	(0.0271)
Exporter_t	0.117***	-0.0327***	0.112***	0.0674**	0.115***	0.000137	0.00121
	(0.0260)	(0.0111)	(0.0258)	(0.0338)	(0.0263)	(0.00336)	(0.0134)
$\text{Exporter}_t \times \text{Robots}_t$	0.0111	0.0117	0.0579	-0.0730	0.0248	-0.00197	0.0179
	(0.0505)	(0.0189)	(0.0552)	(0.0681)	(0.0600)	(0.0127)	(0.0232)
Exporter_{t-4}	0.0581**	0.00860	0.0454**	0.0558*	0.0548**	-0.000725	0.0167
	(0.0229)	(0.00902)	(0.0230)	(0.0328)	(0.0233)	(0.00279)	(0.0121)
$\text{Exporter}_{t-4} \times \text{Robots}_{t-4}$	0.0530	-0.0476**	0.0714	0.112	0.0561	-0.00429	0.00283
	(0.0484)	(0.0233)	(0.0499)	(0.0715)	(0.0543)	(0.0115)	(0.0310)
Observations	4572	4541	4549	4549	4565	4565	4532
R-squared	0.211	0.164	0.219	0.143	0.212	0.062	0.615
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. Export is an indicator variable equal to firm reports positive exports in the specific year. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.14: Labor market effects of robot adoption – the role of exports: Propensity score

	Employment	Labor cost share	Low-skilled	High-skilled	Manufacturing employment	Share of manuf. employment	Average wage
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)
Robots_t	0.0639	-0.0373*	0.0481	0.122**	0.0655	0.00569	-0.000775
	(0.0397)	(0.0210)	(0.0381)	(0.0617)	(0.0409)	(0.00709)	(0.0242)
Robots_{t-4}	0.0205	-0.0260	0.00435	0.0128	0.0268	0.00241	-0.0173
	(0.0473)	(0.0248)	(0.0436)	(0.0770)	(0.0461)	(0.00654)	(0.0244)
Exporter_t	0.105***	-0.0348***	0.0959***	0.0630*	0.110***	0.00447	0.00309
	(0.0261)	(0.0122)	(0.0258)	(0.0348)	(0.0267)	(0.00448)	(0.0147)
$\text{Exporter}_t \times \text{Robots}_t$	-0.00298	0.0189	0.0450	-0.122	-0.0201	-0.0156*	0.0223
	(0.0542)	(0.0239)	(0.0539)	(0.0785)	(0.0557)	(0.00859)	(0.0298)
Exporter_{t-4}	0.0639**	0.00833	0.0487*	0.0412	0.0713***	0.00539	0.0237*
	(0.0255)	(0.0105)	(0.0258)	(0.0363)	(0.0257)	(0.00374)	(0.0135)
$\text{Exporter}_{t-4} \times \text{Robots}_{t-4}$	0.0678	-0.00525	0.0888	0.0839	0.0563	-0.0107	0.00504
	(0.0596)	(0.0265)	(0.0588)	(0.0916)	(0.0594)	(0.00772)	(0.0318)
Observations	4626	4589	4605	4605	4618	4618	4579
R-squared	0.218	0.206	0.228	0.158	0.248	0.117	0.664
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. Export is an indicator variable equal to firm reports positive exports in the specific year. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.15: Output effects of robot adoption (alternative propensity scores)

	Output (in logs)			
	(1)	(2)	(3)	(4)
Robots_t	0.109**	0.121**	0.0937**	0.0958*
	(0.0431)	(0.0484)	(0.0437)	(0.0529)
Robots_{t-4}	0.116***	0.0465	0.111***	0.0458
	(0.0410)	(0.0589)	(0.0420)	(0.0603)
Robots_{t+4}		0.0491		0.0377
		(0.0486)		(0.0518)
Observations	4654	2641	4672	2650
R-squared	0.253	0.268	0.253	0.265
Selection controls	No	No	No	No
Propensity score A	Yes	Yes	No	No
Propensity score B	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes

Notes: Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. The dependent variable in all columns is the log of the firm's deflated output value. Propensity score A includes stock of innovations (computer programs attached to manufacturing processes), real capital stock and investments in machinery as additional variables used in the propensity scores estimation (relative to the main text specification). Propensity score B additionally accounts for the share of manufacturing workers. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.16: Labor market effects of robot adoption (alternative propensity scores)

	Employment	Labor cost share	Low-skilled	High-skilled	Manufacturing employment	Share of manuf. employment	Average wage
Propensity Score A	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)
Robots_t	0.0423	-0.0228**	0.0516*	0.0443	0.0382	-0.00105	0.0114
	(0.0295)	(0.0116)	(0.0310)	(0.0445)	(0.0300)	(0.00473)	(0.0197)
Robots_{t-4}	0.0750**	-0.0212	0.0739**	0.0580	0.0753**	-0.00411	-0.0148
	(0.0335)	(0.0135)	(0.0339)	(0.0582)	(0.0320)	(0.00560)	(0.0199)
Observations	4654	4616	4634	4634	4646	4646	4606
R-squared	0.194	0.193	0.205	0.152	0.232	0.114	0.655
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Propensity Score B	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)
Robots_t	0.0211	-0.0228**	0.0311	0.0358	0.0192	-0.000652	0.0149
	(0.0326)	(0.0109)	(0.0337)	(0.0439)	(0.0324)	(0.00401)	(0.0213)
Robots_{t-4}	0.0689*	-0.0260**	0.0708**	0.0327	0.0727**	-0.00245	-0.0254
	(0.0352)	(0.0122)	(0.0350)	(0.0570)	(0.0336)	(0.00548)	(0.0199)
Observations	4672	4634	4652	4652	4665	4665	4624
R-squared	0.199	0.198	0.212	0.140	0.234	0.098	0.655
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. Propensity score A includes stock of innovations (computer programs attached to manufacturing processes), real capital stock and investments in machinery as additional variables used in the propensity scores estimation (relative to the main text specification). Propensity score B additionally accounts for the share of manufacturing workers. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.17: Robot adoption and intra-industry reallocations

	ESEE		IFR	
PANEL: Exit in $t+1$	(1c)	(2c)	(3c)	(4c)
Robot-density$_t$	0.0313*	0.0334	0.00383	0.0123**
	(0.0188)	(0.0301)	(0.00467)	(0.00610)
Robot-density$_t$ $\times$ Robots$_t$	-0.0530**	-0.0659*	-0.00428	-0.00639
	(0.0256)	(0.0350)	(0.00367)	(0.00479)
Robots$_t$	0.0210	0.0856**	0.0245	0.0795*
	(0.0148)	(0.0400)	(0.0258)	(0.0443)
Observations	9274	4168	7566	3997
R-squared	0.030	0.040	0.034	0.039
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Selection controls	No	Yes	No	Yes
Industry controls + interact.	No	Yes	No	Yes

Notes: In columns (1) to (3) we define robot density as the share of sales attributable to robot-using firms in total industry sales constructed from the ESEE data. In columns (4) to (6) we use the stock of robots in an industry (in logs) constructed from the IFR data. The variable robots is a 0/1 indicator variable equal to one if the firm uses robots in the sample year, and zero otherwise. We use a 0/1 indicator variable as the dependent variable; this variable is equal to one if the firm exits the market in the next period, and zero if it continues its operations. Selection controls include the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), exporter status, importer status, and foreign ownership status (all in *t-4*). We add one to all factor intensity variables before taking logs in order to keep zero observations. Industry controls are annual industry averages of capital, skill, and R&D intensity; these variable are also interacted with the firm-specific robot-use dummy variable. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.11 Alternative systems in the production process

As stated in Section 2 of the paper, we exploit information on the use of robots from the following survey question: *"State whether the production process uses any of the following systems: 1. Computer-digital machine tools; 2. Robotics; 3. Computer-assisted design; 4. Combination of some of the above systems through a central computer (CAM, flexible manufacturing systems, etc.); 5. Local Area Network (LAN) in manufacturing activity"*. In the following, we show that the effects of robot adoption are different from those associated with alternative systems included in the survey question. We create three additional indicator variables from the survey question, labelled CAM, CAD, and FLEX, respectively. They are defined as 0/1 indicator variables equal to one if the firm uses computer-digital machine tools (CAM), computer-assisted design (CAD), or a combination of systems through a central computer (FLEX). Table A.18 provides summary statistics on these indicator variables along with our robot dummy variable from the main text. Table A.19 shows correlations among the four indicator variables. We see from these statistics that robots are used less frequently in the production process than the other three alternative systems. We also see slightly positive pairwise correlations among all variables.

Table A.18: Descriptive statistics on systems in the production process

	Mean	STD.	Obs.
Robot	0.086	0.281	12808
CAM	0.358	0.479	12808
CAD	0.266	0.442	12808
FLEX	0.244	0.430	12808

Notes: Robots, CAM, CAD or FLEX are construct as 0/1 indicator variables equal to one if the firm uses robotics (Robot), computer-digital machine tools (CAM), computer-assisted design (CAD), or, combination of some of the above systems through a central computer (FLEX).

Table A.19: Correlations among different systems in the production process

	Robot	CAM	CAD	FLEX
Robot	1.000			
CAM	0.199*	1.000		
CAD	0.195*	0.330*	1.000	
FLEX	0.114*	0.200*	0.126*	1.000

Notes: Robots, CAM, CAD or FLEX are construct as 0/1 indicator variables equal to one if the firm uses robotics (Robot), computer-digital machine tools (CAM), computer-assisted design (CAD), or, combination of some of the above systems through a central computer (FLEX), where * $p < 0.01$.

To estimate the output effects associated with the use of different technologies, we follow the exact same strategy as in Section 5.1 of our paper. Specifically, we estimate Eq. (3) but replace the robots indicator with our indicators for CAM, CAD, and FLEX, respectively. In Tables A.20, A.21, and A.22, we report our estimates based on samples of firms that, respectively, do not use CAM, CAD, or FLEX in the first year they appear in the sample. It turns out that both the adoption of computer-digital machine tools and of flexible manufacturing systems through a central computer raise firm output. However, the magnitudes of the effects are smaller than in the case of robot adoption. Adopting computer-assisted designs turns out to have no statistically significant effect on output, although the relevant coefficients are estimated with a positive sign. We also investigated whether the output effects of robot adoption reported in the main text of our paper are robust to controlling for alternative systems in the production process. Table A.23 reports the estimates. The results are striking. We find that including the additional controls has no impact on the significance and the size of our estimated coefficients for robot adoption. At the same time, we find that the coefficients of the alternative systems are much smaller than before and, with few exceptions, insignificant.

Table A.20: Output effects of computer-digital machine tools

	Output (in logs)			
	(1)	(2)	(3)	(4)
CAM_t	0.0661**	0.105***	0.0657**	0.106***
	(0.0278)	(0.0343)	(0.0289)	(0.0350)
CAM_{t-4}	0.0794***	0.0865**	0.0870***	0.0766**
	(0.0287)	(0.0337)	(0.0295)	(0.0346)
CAM_{t+4}		0.0584		0.0350
		(0.0382)		(0.0382)
Observations	3477	1898	3185	1736
R-squared	0.288	0.343	0.300	0.350
Selection controls	No	No	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes

Notes: CAM is a 0/1 indicator variable equal to one if the firm uses computer-digital machine tools in a period t. The dependent variable in all columns is the log of the firm's deflated output. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. The sample is restricted to firms that do not use CAM in the first year they appear in the sample. Robust standard errors are clustered by firm and given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

We then proceed by investigating the labor market affects of these alternative systems following our strategy from the main text. Table A.24 reports the effects of adopting CAM, CAD, and FLEX, respectively. We find positive and significant employment effects for all three systems. However, the most striking difference when comparing the results for these alternative systems with those of robots is that only the latter reduce the firm's labor cost share, as is evident from columns (2a), (2b), and (2c) in Table A.24. When introducing the alternative systems as further control variables in our estimations of the labor market effects of robots, we find that this has virtually no impact on the size and significance of our coefficient estimates; see Tables A.25 and A.26 for estimates with selection controls and propensity score reweighting, respectively.

Table A.21: Output effects of computer-assisted design

	Output (in logs)			
	(1)	(2)	(3)	(4)
CAD_t	0.0223	0.0269	0.0276	0.0318
	(0.0340)	(0.0397)	(0.0370)	(0.0436)
CAD_{t-4}	0.0535	0.0702	0.0503	0.0584
	(0.0356)	(0.0448)	(0.0371)	(0.0463)
CAD_{t+4}		-0.0255		-0.0241
		(0.0398)		(0.0398)
Observations	4493	2532	4115	2326
R-squared	0.219	0.284	0.232	0.285
Selection controls	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes

Notes: CAD is a 0/1 indicator variable equal to one if the firm uses computer-assisted design in a period t. The dependent variable in all columns is the log of the firm's deflated output. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. The sample is restricted to firms that do not use CAD in the first year they appear in the sample. Robust standard errors are clustered by firm and given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.22: Output effects of flexible manufacturing systems

	Output (in logs)			
	(1)	(2)	(3)	(4)
FLEX_t	0.0845***	0.0712*	0.0797**	0.0654*
	(0.0308)	(0.0368)	(0.0315)	(0.0394)
FLEX_{t-4}	0.0969**	0.100*	0.0926**	0.0996*
	(0.0395)	(0.0553)	(0.0426)	(0.0593)
FLEX_{t+4}		-0.0134		-0.00645
		(0.0358)		(0.0378)
Observations	3366	1743	3131	1620
R-squared	0.287	0.321	0.309	0.340
Selection controls	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes

Notes: FLEX is a 0/1 indicator variable equal to one if the firm uses flexible manufacturing systems through a central computer in a period t. The dependent variable in all columns is the log of the firm's deflated output. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. The sample is restricted to firms that do not use FLEX in the first year they appear in the sample. Robust standard errors are clustered by firm and given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.23: Output effects of robot adoption controlling for other systems in the production process

	Output (in logs)					
	(1)	(2)	(3)	(4)	(5)	(6)
Robots_t	0.157***	0.106***	0.162***	0.120***	0.126***	0.119**
	(0.0289)	(0.0344)	(0.0315)	(0.0370)	(0.0385)	(0.0495)
Robots_{t-4}	0.121***	0.126***	0.119***	0.111**	0.121***	0.0815
	(0.0325)	(0.0446)	(0.0337)	(0.0468)	(0.0415)	(0.0545)
Robots_{t+4}		0.0743**		0.0471		0.0724
		(0.0348)		(0.0383)		(0.0478)
CAM_t	0.0436*	0.0340	0.0422*	0.0247	0.0671**	0.0476
	(0.0232)	(0.0299)	(0.0236)	(0.0304)	(0.0275)	(0.0351)
CAM_{t-4}	0.0297	-0.00699	0.0255	-0.0190	0.0332	-0.0203
	(0.0227)	(0.0272)	(0.0233)	(0.0279)	(0.0252)	(0.0308)
CAM_{t+4}		0.00971		-0.00130		0.0502
		(0.0282)		(0.0295)		(0.0323)
CAD_t	0.0189	0.00583	0.00546	-0.00641	-0.0219	-0.0296
	(0.0292)	(0.0365)	(0.0324)	(0.0410)	(0.0396)	(0.0464)
CAD_{t-4}	0.00805	0.0238	0.00372	0.0128	-0.0172	0.0209
	(0.0273)	(0.0351)	(0.0291)	(0.0362)	(0.0311)	(0.0415)
CAD_{t+4}		-0.0216		-0.00727		-0.0168
		(0.0355)		(0.0380)		(0.0439)
FLEX_t	0.0256	0.0334	0.0250	0.0401	0.0207	0.0256
	(0.0255)	(0.0283)	(0.0266)	(0.0285)	(0.0281)	(0.0350)
FLEX_{t-4}	-0.00607	-0.00357	-0.00972	-0.0122	-0.0232	-0.00480
	(0.0217)	(0.0257)	(0.0238)	(0.0290)	(0.0260)	(0.0318)
FLEX_{t+4}		-0.0240		-0.0248		-0.00570
		(0.0286)		(0.0283)		(0.0361)
Observations	4977	2813	4570	2574	4633	2634
R-squared	0.240	0.295	0.249	0.294	0.264	0.284
Selection controls	No	No	Yes	Yes	No	No
Propensity scores	No	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robots is a 0/1 indicator variable equal to one if the firm uses robots in a period t. CAM is a 0/1 indicator variable equal to one if the firm uses computer-digital machine tools in a period t. CAD is a 0/1 indicator variable equal to one if the firm uses computer-assisted design in a period t. FLEX is a 0/1 indicator variable equal to one if the firm uses flexible manufacturing systems through a central computer in a period t. The dependent variable in all columns is the log of the firm's deflated output. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are clustered by firm and given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.24: Labor market effects of different systems in the production process

	Employment	Labor cost share	Low-skilled	High-skilled	Manufacturing employment	Share of manuf. employment	Average wage
Computer-digital machine tools	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)
CAM_t	0.0690***	0.00637	0.0578***	0.0814**	0.0545**	-0.00760**	0.00954
	(0.0222)	(0.00692)	(0.0219)	(0.0353)	(0.0233)	(0.00366)	(0.0105)
CAM_{t-4}	0.0557**	-0.00499	0.0447*	0.0580*	0.0349	-0.0117**	0.0167
	(0.0247)	(0.00918)	(0.0250)	(0.0349)	(0.0275)	(0.00559)	(0.0113)
Observations	3187	3168	3165	3165	3181	3181	3160
R-squared	0.274	0.201	0.280	0.162	0.253	0.076	0.656
Computer-assisted design	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)
CAD_t	0.0209	0.00386	0.0213	0.0704*	0.0358	0.00570	0.0232*
	(0.0291)	(0.00994)	(0.0285)	(0.0392)	(0.0260)	(0.00611)	(0.0139)
CAD_{t-4}	0.0725***	-0.0000145	0.0612**	0.0694*	0.0686**	-0.00548	-0.00371
	(0.0261)	(0.0122)	(0.0260)	(0.0384)	(0.0267)	(0.00479)	(0.0125)
Observations	4116	4092	4089	4089	4108	4108	4084
R-squared	0.214	0.150	0.219	0.127	0.212	0.047	0.631
Flexible manufacturing systems	(1c)	(2c)	(3c)	(4c)	(5c)	(6c)	(7c)
$FLEX_t$	0.0796***	0.00309	0.0806***	0.0665	0.0811***	0.00146	-0.0106
	(0.0260)	(0.0107)	(0.0263)	(0.0447)	(0.0270)	(0.00449)	(0.0122)
$FLEX_{t-4}$	0.0955***	-0.00175	0.865***	0.137***	0.107***	0.00131	-0.0127
	(0.0288)	(0.0148)	(0.0288)	(0.0445)	(0.0296)	(0.00601)	(0.0144)
Observations	3132	3111	3112	3112	3130	3130	3105
R-squared	0.274	0.212	0.285	0.164	0.261	0.088	0.645
Selection controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. CAM is a 0/1 indicator variable equal to one if the firm uses computer-digital machine tools in the specified period. CAD is a 0/1 indicator variable equal to one if the firm uses computer-assisted design in the specified period. FLEX is a 0/1 indicator variable equal to one if the firm uses flexible manufacturing systems through a central computer in the specified period. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. The sample is restricted to firms that do not use CAM, CAD, or FLEX in the first year they appear in the sample, respectively. Robust standard errors are clustered by firm and given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.25: Labor market effects of robot adoption controlling for other systems in the production process - Selection controls

	(1) Employment	(2) Labor cost share	(3) Low-skilled	(4) High-skilled	(5) Manufacturing employment	(6) Share of manuf. employment	(7) Average wage
Robots_t	0.0436*	-0.0387***	0.0468*	0.0613	0.0262	-0.00630	-0.00431
	(0.0249)	(0.00900)	(0.0258)	(0.0388)	(0.0274)	(0.00529)	(0.0121)
Robots_{t-4}	0.0424*	-0.0334***	0.0358	0.0907**	0.0413	-0.00329	-0.0132
	(0.0253)	(0.0121)	(0.0259)	(0.0395)	(0.0264)	(0.00497)	(0.0161)
CAM_t	0.0367**	-0.000974	0.0282	0.0389	0.0277	-0.00311	0.00108
	(0.0175)	(0.00745)	(0.0176)	(0.0272)	(0.0177)	(0.00312)	(0.00918)
CAM_{t-4}	0.0127	-0.00274	-0.00203	0.0455*	-0.000722	-0.00817***	0.0109
	(0.0179)	(0.00728)	(0.0180)	(0.0252)	(0.0188)	(0.00313)	(0.00935)
CAD_t	0.0257	0.0122	0.0410	0.0412	0.0427*	0.00542	0.0160
	(0.0253)	(0.00867)	(0.0293)	(0.0359)	(0.0226)	(0.00538)	(0.0131)
CAD_{t-4}	0.0558**	0.00880	0.0489**	0.0423	0.0560**	-0.00133	-0.00919
	(0.0219)	(0.00995)	(0.0219)	(0.0318)	(0.0219)	(0.00356)	(0.0116)
FLEX_t	0.0144	0.0000360	0.00777	0.0108	0.0122	-0.00243	-0.00832
	(0.0192)	(0.00734)	(0.0206)	(0.0334)	(0.0219)	(0.00485)	(0.00968)
FLEX_{t-4}	0.00390	0.00848	-0.00856	0.0301	0.00705	0.00169	-0.00824
	(0.0166)	(0.00807)	(0.0178)	(0.0276)	(0.0175)	(0.00380)	(0.00959)
Observations	4572	4541	4549	4549	4565	4565	4532
R-squared	0.207	0.160	0.214	0.145	0.208	0.066	0.616
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. CAM is a 0/1 indicator variable equal to one if the firm uses computer-digital machine tools in the specified period. CAD is a 0/1 indicator variable equal to one if the firm uses computer-assisted design in the specified period. FLEX is a 0/1 indicator variable equal to one if the firm uses flexible manufacturing systems through a central computer in the specified period. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are clustered by firm and given in parentheses.. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.26: Labor market effects of robot adoption controlling for other systems in the production process - Propensity score

	(1) Employment	(2) Labor cost share	(3) Low-skilled	(4) High-skilled	(5) Manufacturing employment	(6) Share of manuf. employment	(7) Average wage
Robots$_t$	0.0480*	-0.0287**	0.0605**	0.0412	0.0375	-0.00331	0.0109
	(0.0273)	(0.0117)	(0.0283)	(0.0437)	(0.0287)	(0.00491)	(0.0164)
Robots$_{t-4}$	0.0618*	-0.0334**	0.0672*	0.0399	0.0629*	-0.00247	-0.0151
	(0.0359)	(0.0151)	(0.0360)	(0.0503)	(0.0353)	(0.00549)	(0.0184)
CAM$_t$	0.0524**	-0.0101	0.0409*	0.0366	0.0483**	-0.000456	-0.000396
	(0.0209)	(0.00788)	(0.0211)	(0.0293)	(0.0216)	(0.00263)	(0.0103)
CAM$_{t-4}$	0.00853	-0.00262	-0.00893	0.0686**	0.00216	-0.00529	0.0210*
	(0.0194)	(0.00705)	(0.0197)	(0.0277)	(0.0191)	(0.00453)	(0.0112)
CAD$_t$	0.0207	0.0136	0.0449	0.0194	0.0501**	0.0104	-0.00509
	(0.0332)	(0.00955)	(0.0407)	(0.0397)	(0.0243)	(0.00801)	(0.0149)
CAD$_{t-4}$	0.0389	0.0141	0.0244	0.0539	0.0414	-0.00215	-0.00880
	(0.0250)	(0.0109)	(0.0263)	(0.0431)	(0.0252)	(0.00374)	(0.0126)
FLEX$_t$	0.0129	0.00845	0.00196	0.0176	0.00224	-0.00982**	-0.00467
	(0.0225)	(0.00917)	(0.0234)	(0.0437)	(0.0236)	(0.00495)	(0.0117)
FLEX$_{t-4}$	0.00370	0.0197*	-0.0117	0.0410	0.00214	-0.00250	0.00207
	(0.0201)	(0.0103)	(0.0224)	(0.0336)	(0.0195)	(0.00387)	(0.0107)
Observations	4632	4595	4611	4611	4624	4624	4585
R-squared	0.214	0.206	0.226	0.163	0.244	0.126	0.663
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. CAM is a 0/1 indicator variable equal to one if the firm uses computer-digital machine tools in the specified period. CAD is a 0/1 indicator variable equal to one if the firm uses computer-assisted design in the specified period. FLEX is a 0/1 indicator variable equal to one if the firm uses flexible manufacturing systems through a central computer in the specified period. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are clustered by firm and given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.12 Regression results for two different samples

Here we present estimation results akin to the one presented throughout Sections 4 and 5 for two different samples. In a first sample we include all 644 firms that start to use robots, even though some of them switch back and forth several times, see Table A.27 for the selection analysis and Tables A.28 and A.29 for the treatment analysis. In a second sample we restrict the focus only on those 397 firms that start to use robots and continuously report to use robots in the production process afterwards, see Table A.30 for the selection analysis and Tables A.31 and A.32 for the treatment analysis.

Table A.27: Selection into robot adoption: Cross-sectional specification – all firms

	Robot adoption (0/1 indicator)						
Base year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output	0.0352***	0.0406***	0.0293***	0.0345***	0.0376***	0.0400***	0.0447***
	(0.00533)	(0.00606)	(0.00617)	(0.00677)	(0.00720)	(0.00748)	(0.00965)
Labor productivity					-0.0111	-0.00414	0.0138
					(0.0120)	(0.0129)	(0.0181)
Skill intensity		-0.331***		-0.317**	-0.348***	-0.337**	-0.225
		(0.126)		(0.132)	(0.132)	(0.132)	(0.148)
Share of manu-facturing workers		0.289**		0.278**	0.280**	0.281**	0.247*
		(0.116)		(0.121)	(0.122)	(0.123)	(0.137)
Share of production workers		0.0453*		0.0471*	0.0481*	0.0446*	0.0247
		(0.0240)		(0.0247)	(0.0249)	(0.0251)	(0.0319)
Exporter			0.0360**	0.0363**	0.0371**	0.0380**	0.0554***
			(0.0162)	(0.0167)	(0.0167)	(0.0168)	(0.0211)
Assimilation of foreign . technologies			0.0463*	0.0318	0.0303	0.0296	-0.00597
			(0.0240)	(0.0247)	(0.0249)	(0.0249)	(0.0371)
Importer			0.0101	0.0186	0.0154	0.0134	0.00462
			(0.0161)	(0.0169)	(0.0170)	(0.0170)	(0.0230)
Foreign owned			-0.0310	-0.0330	-0.0375	-0.0372	-0.0617
			(0.0292)	(0.0298)	(0.0301)	(0.0303)	(0.0422)
Capital intensity	0.0203***	0.0188***	0.0188***	0.0179**	0.0181**	0.0192***	0.0123
	(0.00663)	(0.00701)	(0.00670)	(0.00708)	(0.00723)	(0.00735)	(0.00890)
R&D intensity	0.0174	0.0291	0.00750	0.0215	0.0226	0.0222	-0.0175
	(0.0198)	(0.0206)	(0.0202)	(0.0210)	(0.0215)	(0.0215)	(0.0240)
Average wage						-0.0340	-0.0879***
						(0.0237)	(0.0331)
Interest rate							0.00001
							(0.0037)
Observations	3611	3434	3494	3322	3283	3266	1506
R-squared	0.160	0.166	0.159	0.164	0.168	0.168	0.213

Notes: The dependent variable in all columns is a 0/1 indicator variable equal to one if the firm adopts robots during our sample period and zero otherwise. Output is the firm's deflated output value (in logs). Labor productivity is the firm's deflated value added per worker (in logs). Skill intensity is the firm's share of workers with a five-year university degree (in logs). Share manufacturing is the firm's share of manufacturing workers (in logs). Share production is the firm's share of production workers (in logs). Exporter is a dummy variable for positive exports. Assimilation of foreign tech. is a dummy variable indicating whether the firm assimilated foreign technologies. Importer is a dummy variable for positive imports. Foreign owned is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Capital intensity is defined as the firm's deflated capital stock per worker (in logs). R&D intensity is defined as the firm's deflated R&D expenditures relative to its deflated total sales (in logs). Average wage is defined as the firm's labor costs divided by the total number of workers (in logs). Interest rate is defined as the firm's interest rate on short-term dept (in percent). All estimates include industry-base-year fixed effects. We add one to all factor intensity variables before taking logs in order to keep zero observations. Therefore, all estimates include dummy variables (not reported) equal to one whenever the respective factor intensity variable is equal to zero before adding one. All explanatory variables are measured in the base year defined as the first year the firm appears in the sample. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.28: Output effects of robot adoption – all firms

	Output (in logs)					
	(1)	(2)	(3)	(4)	(5)	(6)
Robots$_t$	0.125***	0.0938***	0.139***	0.103***	0.0982***	0.0880**
	(0.0257)	(0.0300)	(0.0282)	(0.0329)	(0.0345)	(0.0447)
Robots$_{t-4}$	0.0906***	0.0833**	0.0918***	0.0695*	0.113***	0.0816*
	(0.0288)	(0.0354)	(0.0309)	(0.0372)	(0.0361)	(0.0427)
Robots$_{t+4}$		0.0631**		0.0359		0.0910**
		(0.0295)		(0.0326)		(0.0416)
Observations	5283	3044	4855	2788	4791	2761
R-squares	0.239	0.300	0.252	0.296	0.264	0.288
Selection controls	No	No	Yes	Yes	No	No
Propensity scores	No	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. The dependent variable in all columns is the log of the firm's deflated output value. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.29: Labor market effects of robot adoption – all firms

	Employment	Labor cost share	Low-skilled	High-skilled	Manufacturing employment	Share of manuf. employment	Average wage
PANEL A: Selection Controls	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)
Robots_t	0.0543**	-0.0296***	0.0539**	0.0534	0.0370	-0.00744	-0.00267
	(0.0220)	(0.00755)	(0.0226)	(0.0339)	(0.0243)	(0.00492)	(0.0102)
Robots_{t-4}	0.0462**	-0.0205**	0.0373*	0.0970***	0.0446*	-0.00285	-0.00778
	(0.0219)	(0.00899)	(0.0223)	(0.0320)	(0.0229)	(0.00404)	(0.0130)
Observations	4857	4825	4830	4830	4850	4850	4816
R-squared	0.202	0.156	0.210	0.142	0.203	0.054	0.625
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PANEL B: Propensity Score	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)
Robots_t	0.0548**	-0.0180*	0.0625**	0.0485	0.0392	-0.00724	0.00238
	(0.0248)	(0.00971)	(0.0257)	(0.0389)	(0.0274)	(0.00613)	(0.0152)
Robots_{t-4}	0.0600*	-0.0242**	0.0606*	0.0559	0.0596*	-0.00293	-0.00851
	(0.0314)	(0.0111)	(0.0312)	(0.0413)	(0.0314)	(0.00450)	(0.0151)
Observations	4790	4751	4765	4765	4781	4781	4741
R-squared	0.210	0.202	0.224	0.157	0.237	0.120	0.669
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.30: Selection into robot adoption: Cross-sectional specification – continuous adoption firms

	Robot adoption (0/1 indicator)						
Base year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output	0.0325***	0.0365***	0.0282***	0.0323***	0.0357***	0.0387***	0.0376***
	(0.00475)	(0.00541)	(0.00552)	(0.00604)	(0.00643)	(0.00667)	(0.00907)
Labor productivity					-0.0136	-0.00508	0.0222
					(0.0105)	(0.0111)	(0.0170)
Skill intensity		-0.297***		-0.287**	-0.314***	-0.301***	-0.159
		(0.111)		(0.115)	(0.113)	(0.112)	(0.139)
Share of manufacturing workers		0.184*		0.158	0.160	0.160	0.183
		(0.107)		(0.112)	(0.113)	(0.115)	(0.130)
Share of production workers		0.0209		0.0177	0.0169	0.0125	0.0176
		(0.0223)		(0.0230)	(0.0233)	(0.0234)	(0.0311)
Exporter			0.0254*	0.0252*	0.0237	0.0245*	0.0389*
			(0.0143)	(0.0147)	(0.0148)	(0.0148)	(0.0201)
Assimilation of foreign technologies			0.0492**	0.0374	0.0337	0.0328	0.0109
			(0.0223)	(0.0228)	(0.0230)	(0.0231)	(0.0357)
Importer			0.00469	0.00988	0.00918	0.00710	-0.00682
			(0.0141)	(0.0149)	(0.0150)	(0.0150)	(0.0218)
Foreign owned			-0.0276	-0.0381	-0.0376	-0.0365	-0.0554
			(0.0275)	(0.0281)	(0.0285)	(0.0286)	(0.0414)
Capital intensity	0.0143***	0.0130**	0.0127**	0.0119**	0.0126**	0.0142**	0.0115
	(0.00553)	(0.00584)	(0.00562)	(0.00595)	(0.00605)	(0.00613)	(0.00812)
R&D intensity	0.00556	0.0132	-0.00415	0.00437	0.00556	0.00510	-0.00745
	(0.0183)	(0.0190)	(0.0188)	(0.0195)	(0.0200)	(0.0200)	(0.0225)
Average wage						-0.0428**	-0.0837***
						(0.0200)	(0.0315)
Interest rate							0.0011
							(0.0034)
Observations	3391	3220	3289	3122	3086	3069	1473
R-squared	0.149	0.153	0.147	0.148	0.154	0.155	0.197

Notes: The dependent variable in all columns is a 0/1 indicator variable equal to one if the firm adopts robots during our sample period and zero otherwise. Output is the firm's deflated output value (in logs). Labor productivity is the firm's deflated value added per worker (in logs). Skill intensity is the firm's share of workers with a five-year university degree (in logs). Share manufacturing is the firm's share of manufacturing workers (in logs). Share production is the firm's share of production workers (in logs). Exporter is a dummy variable for positive exports. Assimilation of foreign tech. is a dummy variable indicating whether the firm assimilated foreign technologies. Importer is a dummy variable for positive imports. Foreign owned is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Capital intensity is defined as the firm's deflated capital stock per worker (in logs). R&D intensity is defined as the firm's deflated R&D expenditures relative to its deflated total sales (in logs). Average wage is defined as the firm's labor costs divided by the total number of workers (in logs). Interest rate is defined as the firm's interest rate on short-term dept (in percent). All estimates include industry-base-year fixed effects. We add one to all factor intensity variables before taking logs in order to keep zero observations. Therefore, all estimates include dummy variables (not reported) equal to one whenever the respective factor intensity variable is equal to zero before adding one. All explanatory variables are measured in the base year defined as the first year the firm appears in the sample. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.31: Output effects of robot adoption – continuous adoption firms

	Output (in logs)					
	(1)	(2)	(3)	(4)	(5)	(6)
Robots$_t$	0.198***	0.118**	0.195***	0.124**	0.125**	0.266***
	(0.0398)	(0.0567)	(0.0427)	(0.0627)	(0.0567)	(0.0901)
Robots$_{t-4}$	0.136***	0.119**	0.142***	0.0802	0.158**	0.0556
	(0.0464)	(0.0598)	(0.0481)	(0.0649)	(0.0709)	(0.0952)
Robots$_{t+4}$		0.0990*		0.0772		0.0209
		(0.0506)		(0.0525)		(0.0684)
Observations	4396	2410	4061	2218	4193	2314
R-squared	0.240	0.297	0.252	0.294	0.264	0.290
Selection controls	No	No	Yes	Yes	No	No
Propensity scores	No	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. The dependent variable in all columns is the log of the firm's deflated output value. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.32: Labor market effects of robot adoption – continuous adoption firms

	Employment	Labor cost share	Low-skilled	High-skilled	Manufacturing employment	Share of manuf. employment	Average wage
PANEL A: Selection Controls	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)
Robots_t	0.0596*	-0.0414***	0.0501	0.135***	0.0370	-0.00520	-0.00448
	(0.0339)	(0.0101)	(0.0351)	(0.0497)	(0.0404)	(0.00909)	(0.0152)
Robots_{t-4}	0.0650*	-0.0422***	0.0564	0.0668	0.0642*	-0.00750	-0.0225
	(0.0344)	(0.0125)	(0.0362)	(0.0608)	(0.0367)	(0.00744)	(0.0205)
Observations	4062	4033	4043	4043	4055	4055	4025
R-squared	0.200	0.173	0.206	0.151	0.205	0.066	0.630
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PANEL B: Propensity Score	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)
Robots_t	0.0699*	-0.0163	0.0733*	0.00749	0.0703*	0.00596	0.00623
	(0.0385)	(0.0158)	(0.0388)	(0.0637)	(0.0401)	(0.00912)	(0.0244)
Robots_{t-4}	0.0865	-0.0466**	0.0893	0.0788	0.0786	-0.0124	-0.0210
	(0.0551)	(0.0201)	(0.0580)	(0.0915)	(0.0547)	(0.00926)	(0.0271)
Observations	4192	4156	4173	4173	4184	4184	4147
R-squared	0.209	0.211	0.221	0.166	0.243	0.137	0.670
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.13 Labor market effects of robot adoption – controlling for collective dismissals

Robot adoption can be seen as a disruptive event on employment within firms. In this subsection, we aim to shed further light on the impact of robot adoption on employment, while controlling for collective dismissals within firms. We do so, by using explicit information in the data set on a change in regular workers due to redundancies. Specifically, the survey asks firms (yes/no) whether there has been a significant change in the regular workforce due to a "reduction in the workforce (termination of contracts, early retirement, incentives for leaves of absence, etc.)" over the last year.[60] We use this information to construct an indicator variable equal to one if there was a significant change in the current year. The question has been included in the survey every year since 1993. In less than 9% of all firm-year observations, the indicator variable is equal to one. The mean (SD) of the indicator variable is 0.084 (0.277) for non-adopters and 0.103 (0.304) for robot adopting firms.

In a first step, we investigate whether robot adoption is associated with an in-crease in the likelihood of collective dismissals. To do so, we follow the strategy from Table 2 and use the indicator variable for collective dismissals as an alternative outcome variable. Results presented in Table A.33 indicate no statistically significant and robust (linear) relationship between robot adoption and collective dismissals.

[60]The original wording in Spanish is: "Reducción de plantilla (expedientes con extinción de contratos, jubilaciones anticipadas, bajas incentivada, etc.)"

Table A.33: Robot adoption and the likelihood of collective dismissals

	Collective dismissals					
	(1)	(2)	(3)	(4)	(5)	(6)
Robots_t	0.0190	-0.0337	0.00281	-0.0460*	0.0479**	-0.0268
	(0.0203)	(0.0262)	(0.0198)	(0.0250)	(0.0241)	(0.0397)
Robots_{t-4}	-0.0109	-0.0378	-0.0186	-0.0467	0.0119	-0.0611*
	(0.0218)	(0.0349)	(0.0234)	(0.0369)	(0.0316)	(0.0354)
Robots_{t+4}		-0.0498**		-0.0461*		-0.00318
		(0.0246)		(0.0272)		(0.0267)
Observations	4986	2811	4587	2580	4632	2633
R-squared	0.057	0.090	0.076	0.118	0.101	0.118
Selection controls	No	No	Yes	Yes	No	No
Propensity scores	No	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. The dependent variable in all columns is a 0/1 indicator variable equal to one if there has been a significant change in the regular workforce due to any workforce reduction. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors clustered by firm are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

In a second step, we rerun the estimation from Table 3 while using the indicator variable for collective dismissals in the current and previous years as further control variables. Results from this exercise are presented in Tables A.34 and A.35. Comparing the indicator variable for robots (in t and $t-4$) to the estimated coefficients reported in the main text in Table 3, one can conclude that this does very little to our estimated effects of robot adoption on different labor market outcomes. Furthermore, the estimated coefficients for collective dismissals reveal a negative effect on employment (column 1), which is concentrated among low-skilled (column 3) and manufacturing (column 5) workers. In an additional set of estimates, we also include interaction terms between robot adoption and collective dismissals (in t and $t-4$). It turns out that the interaction terms are not statistically different from zero and do not change the results presented in Tables A.34 and A.35.

Table A.34: Labor market effects of robot adoption controlling for collective dismissals - Selection controls

	(1) Employment	(2) Labor cost share	(3) Low-skilled	(4) High-skilled	(5) Manufacturing employment	(6) Share of manuf. employment	(7) Average wage
Robots_t	0.0591**	-0.0426***	0.0634**	0.0650	0.0464*	-0.00432	-0.00586
	(0.0253)	(0.0107)	(0.0261)	(0.0426)	(0.0280)	(0.00583)	(0.0128)
Robots_{t-4}	0.0272	-0.0375***	0.0190	0.0677*	0.0296	-0.00109	-0.0155
	(0.0263)	(0.0117)	(0.0266)	(0.0408)	(0.0275)	(0.00500)	(0.0170)
CD_t	-0.0455	0.0673***	-0.0347	-0.0109	-0.0347	0.00534	0.0669***
	(0.0279)	(0.0133)	(0.0287)	(0.0425)	(0.0278)	(0.00416)	(0.0167)
CD_{t-1}	-0.132***	0.000419	-0.150***	-0.0501	-0.121***	0.00554	0.00489
	(0.0308)	(0.0115)	(0.0335)	(0.0381)	(0.0293)	(0.00458)	(0.0154)
CD_{t-2}	-0.0843***	0.00480	-0.0941***	-0.0467	-0.0896***	0.00132	0.0209
	(0.0281)	(0.00967)	(0.0329)	(0.0401)	(0.0312)	(0.00565)	(0.0137)
CD_{t-3}	-0.0456	-0.00972	-0.0548	0.0512	-0.0664*	-0.00866	-0.0192
	(0.0312)	(0.0135)	(0.0344)	(0.0482)	(0.0340)	(0.00795)	(0.0183)
CD_{t-4}	-0.0976***	0.0130	-0.102***	0.00330	-0.0625*	0.0161*	-0.0121
	(0.0362)	(0.0146)	(0.0354)	(0.0453)	(0.0373)	(0.00837)	(0.0182)
Observations	3710	3689	3696	3696	3710	3710	3688
R-squared	0.283	0.170	0.290	0.121	0.282	0.075	0.559
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. CD is a 0/1 indicator variable equal to one if there has been a significant change in the regular workforce due to any workforce reduction in the specific period. Selection controls (in $t-4$) are the firm's deflated labor productivity (in logs), deflated capital intensity (in logs), skill intensity (in logs), deflated R&D intensity (in logs), as well as exporter, importer, and foreign ownership dummies. We add one to all factor intensity variables before taking logs in order to keep zero observations. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are clustered by firm and given in parentheses.. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.35: Labor market effects of robot adoption controlling for collective dismissals - Propensity score

	(1) Employment	(2) Labor cost share	(3) Low-skilled	(4) High-skilled	(5) Manufacturing employment	(6) Share of manuf. employment	(7) Average wage
Robots_t	0.0553*	-0.0377***	0.0687**	0.0428	0.0528*	0.000483	-0.00239
	(0.0304)	(0.0139)	(0.0314)	(0.0508)	(0.0314)	(0.00497)	(0.0196)
Robots_{t-4}	0.0592*	-0.0305**	0.0614*	0.0437	0.0589*	-0.00245	-0.0144
	(0.0326)	(0.0153)	(0.0331)	(0.0547)	(0.0321)	(0.00384)	(0.0194)
CD_t	-0.0187	0.0804***	-0.00380	-0.0184	-0.0113	0.00362	0.0635***
	(0.0316)	(0.0170)	(0.0345)	(0.0574)	(0.0301)	(0.00493)	(0.0191)
CD_{t-1}	-0.121***	-0.00889	-0.141***	-0.0384	-0.0960***	0.0114	0.00922
	(0.0376)	(0.0131)	(0.0420)	(0.0485)	(0.0300)	(0.00859)	(0.0196)
CD_{t-2}	-0.104***	0.0156	-0.136***	-0.0176	-0.0975***	0.00499	0.0119
	(0.0336)	(0.0141)	(0.0477)	(0.0501)	(0.0339)	(0.00460)	(0.0167)
CD_{t-3}	-0.0537	-0.00117	-0.0620	0.0633	-0.0573	-0.00166	-0.00895
	(0.0356)	(0.0156)	(0.0408)	(0.0683)	(0.0357)	(0.00552)	(0.0191)
CD_{t-4}	-0.125**	0.0125	-0.140***	0.0311	-0.107**	0.00851	-0.00867
	(0.0495)	(0.0150)	(0.0491)	(0.0586)	(0.0425)	(0.0112)	(0.0187)
Observations	3660	3637	3646	3646	3660	3660	3636
R-squared	0.299	0.223	0.312	0.129	0.324	0.123	0.613
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All dependent variables are expressed in logs except for the labor cost share and the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in the specified period. CD is a 0/1 indicator variable equal to one if there has been a significant change in the regular workforce due to any workforce reduction in the specific period. For details on the propensity score reweighting estimator see the text. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Robust standard errors are clustered by firm and given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.