Robots and Firms*

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Abstract

Modern robots are performing tasks hitherto reserved for humans. This has sparked an intense
debate about potential job losses caused by robots. We study the implications of robot adoption
using a rich panel data-set of Spanish manufacturing firms over a 27-year period (1990-2016).
Our study is the first to exploit explicit information on robot use in the production process
of individual firms. We focus on three central questions: (1) Which firms adopt robots in
their production process? (2) What are the effects of robot adoption on output, employment,
and labor costs in adopting firms? (3) Does increasing robot exposure lead to reallocation
of resources between robot adopting and non-robot adopting firms and how does this affect
total factor productivity (TFP) growth within industries? To answer these questions and guide
our empirical analysis, we look at our data through the lens of recent theoretical advances in
the economic analysis of automation. As for the first question, we establish robust evidence
that ex-ante larger and more productive firms are more likely to adopt robots, while ex-ante
more skill-intensive firms are less likely to do so. In addition, we demonstrate a fundamental
complementarity between globalization and robot adoption since exporters are considerably more
likely to adopt robots than non-exporters. As for the second question, we find that within five
years robot adoption generates substantial output gains in the vicinity of 20-25%, reduces the
labor cost share by 5-7%-points, and leads to net job creation at a rate of 10%, especially among
low- and high-skilled workers. These results are robust to controlling for non-random selection
into robot adoption through a suitable propensity score reweighting estimator, suggesting a
causal interpretation of the effects. Finally, we reveal negative employment effects in those firms
that do not automate their production process. Thereby, the reallocation of resources contributes
substantial to TFP growth within industries.

JEL codes: D22; F14; J24; O14;

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1 Introduction

The rise of robot technology has sparked an intense debate about the labor market effects of robot adoption. A dominant concern in this debate is that robots “steal” jobs from humans. A nascent literature seems to support this view, finding large negative effects of robots on employment and wages across U.S. commuting zones (Acemoglu and Restrepo, 2017). However, a key challenge in this literature is the lack of micro-level information on robot adoption. The few existing studies all resort to macro-level information on robot use by industry, and combine it with local industry composition to construct measures of local robot exposure. While this approach is useful in gauging the local labor market effects of robots, it does not take seriously the possibility that robot technology diffuses slowly through the economy, and that robots are not adopted immediately by all firms. In particular, it provides little insight into the following central questions: (1) Which firms in a given industry are the first to adopt robots? (2) What are the direct labor market effects of robot adoption at the firm level? (3) What are the aggregate implications of firm heterogeneity in robot adoption?

Our paper is the first attempt in the literature to provide answers to these important questions. 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). In contrast to existing studies, our paper uses explicit information on robot use in the production process of individual firms. Figure 1 constructed from the ESEE data-set provides a first indication that firm heterogeneity in the adoption of robots matters greatly for the labor market effects of robot technology. It 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. At the same time, our data reveal that robot adopters were able to reduce their labor cost shares relative to non-adopters; see Figure A.1 in the appendix. 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.

Apparently, the descriptive evidence presented in Figure 1 reveals no causal impact of robotics on the different firm-level outcomes. To credibly disentangle the effects due to treatment versus selection into robot adoption is one of the main objectives of this paper. Before we conduct our empirical analysis, we aim to derive hypotheses on the selection of firms into robot adoption and its...
Figure 1: Evolution of firm-level employment (1990-2016)

Notes: The figure depicts the evolution of average firm employment (measured by the number of workers) in a balanced sample of firms from 1990-2016, separately for robot adopters (solid black line) and non-adopters (dashed grey line). 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.

consequences for firm-level output, labor costs, skill-specific labor demand and for aggregate industry productivity based on a theoretical framework. We build on existing work on robots using a so-called task-based framework, in which automation determines the set of tasks that can be produced by machines (see Acemoglu and Restrepo, 2018a,b). We adopt their production technology and apply it to a firm-level perspective by using a setting with monopolistic competition as in Melitz (2003). Noteworthy, there is a striking similarity between modeling automation and the theoretical literature on offshoring, where 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). That is offshoring “parallels [the] analysis of machines replacing tasks” (see Acemoglu and Autor, 2011, p.69).4 Not surprisingly, it turns out that the decision to automate the production process results in a simple trade-off between lower variable costs coupled with higher fixed costs for robot adoption. Thus, when departing from an approach that is used in recent contributions on modeling automation, we end up in a situation that is well established in the literature. For instance, the derived predictions

4Offshoring papers have deepened our knowledge on the selection of firms into offshoring (see Antràs and Helpman, 2004; Antràs et al., 2006; Egger et al., 2015), have emphasized the importance of a productivity- and displacement effect on labor demand (see Grossman and Rossi-Hansberg, 2008), even in the case of specific skills (see Egger et al., 2016).
are akin to mechanisms described in Bustos (2011) or Antràs and Helpman (2004) and Egger et al. (2015) in settings with heterogeneous firms. Bustos (2011) investigates how trade liberalization affects technology upgrading which reduces marginal production costs to the extent of higher fixed costs. In Antràs and Helpman (2004) and Egger et al. (2015) international sourcing (or offshoring) reduces variable production costs due to substitution of domestic labor with cheap foreign labor, which requires the payment of a fixed cost.

In our empirical analysis we begin by investigating the selection of firms into robot adoption. By using within-firm variation we document three important results. First, ex-ante more productive firms are more likely to automate their production process, which reflects the view that innovations, here in the form of robots, are more valuable in more efficient firms. Second, conditional on size, firms employing a less skilled workforce, are more likely to use robots, which is in line with a view that automatable tasks are especially performed by rather unskilled workers (see Autor et al., 2003). Third, globalization, in the form of exporting and foreign ownership raises the incentives for robot adoption, since internal scale economies can be reaped by serving foreign markets in addition to domestic consumers.

We make use of these economic determinants to control for non-random selection into robot adoption to provide causal estimates in our treatment analysis. In a first step, we find robust evidence for positive and sizable output effects, triggered by robot adoption and a pronounced reduction in the share of labor cost. In combination with our findings on positive selection, our results provide novel evidence how technology upgrading, here in the form of robots, amplifies heterogeneity within industry. Looking at employment effects, we document robust evidence for positive employment effects. Thus, the productivity gains from robot adoption seems to outweigh the negative displacement effect of robots replacing human capital. Looking at the composition of skills we find positive employment effects especially for low- and high-skilled workers but no change in medium-skilled jobs, speaking slightly to job-polarization due to robot adoption.

In a final step we investigate how increasing robot exposure leads to reallocation of resources between robot adopting and non-robot adopting firms and how this affects total factor productivity (TFP) growth within industries.

Our paper contributes to recent studies on robots. The seminal paper by Frey and Osborne (2017) was one of the first to examine how susceptible jobs are to computerization in general and predict that almost 47% of total US employment to be automated in the nearest future with a high degree of probability. In Frey and Osborne (2017) computerization is defined as a job automation by means of computer-controlled equipment, hence, it is slightly different from what industrial robots have to offer. Three recent contributions focus specifically on robot adoption by using variation across countries and industries employing data from the International Federation of Robotics (IFR). By covering the period 1993 to 2007 for 17 different countries Graetz and Michaels (2018) find that the growing intensity of robot use accounted for 15% of aggregate economy-wide productivity growth, contributes to growth in wages while employment remains relatively unchanged. In Acemoglu and Restrepo (2017) and Dauth et al. (2018) authors use a local labor
markets approach to estimate the effects of robots on employment, wages, and the composition of jobs. Focusing on the US between 1990 and 2007, Acemoglu and Restrepo (2017) 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 US commuting zones. Looking at Germany between 1994 and 2014, Dauth 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 robot usage 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. We lack knowledge about the selection of firms into robot adoption and its implications on firm-level productivity and labor demand (also see Raj and Seamans, 2018, in highlighting the need for firm-level data). Our study documents strong selection based on observable firms characteristics (size, skill intensity and exporting) and reveals positive employment and output effects in those firms that start to adopt robots. Furthermore, we reveal that the documented productivity gains in Graetz and Michaels (2018) or Dauth et al. (2018) could be partly explained by reallocation of workers from least towards more productive firms. Put differently, with selection of more productive firms into robot adoption, increased exposure to robots reduces market shares of non-robot adopters and even forces the least productive firms to exit. Thus, similar to Melitz (2003) in the context of trade liberalization, this inter-firm reallocation affects aggregate industry productivity. Taking stock, by using detailed firm-panel data from Spain for almost three decades our paper allows to fill an important gap in recent attempts to investigate how automation affects productivity and labor markets. To the best of our knowledge, this is the first study exploring firm-level variation in robots.5

By documenting a positive link between robot adoption and globalization, we speak to a large literature on technology upgrading in a globalized world. Bustos (2011) provide evidence that exporters intensify their investments in technology after a trade liberalization process. Similar Lileeva and Trefler (2010) document how improved foreign market access prompted plants in Canada to adopt more advanced technologies. Speaking to the ownership structure of firms, Guadalupe et al. (2012) and Koch and Smolka (2019) document how changes in ownership leads to process innovation that is triggered by access to foreign markets provided by a foreign parent. Our study complements these findings by looking at a specific type of innovation, that is robots. Even though, we do not claim to find a causal impact of exporting or foreign ownership, we document that both are important determinants for selection into robot adoption. This speaks to the view that serving more consumers allows to scale up the output with positive incentives for installing cost-saving robots. Finally, by finding evidence that imports are a significant selection determinant, we also speak to the literature on importing and technology upgrading as in Bøler et al. (2015) or Bernard et al.

One exception is a study prepared for the European Commission by Jäger et al. (2015). Relying on firm-level data from the European Manufacturing Survey, they document selection and treatment results that are in line with our findings. However, by relying on cross-sectional variation, they are not able to employ within-firm variation and control for non-random selection into robot adoption.
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. In Section 6 we bring our results together by shedding light on the aggregate implications of robot adoption. 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 firm’s 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 facts, drawn from our data, about robot diffusion and robot adoption in Spanish manufacturing.

Our study exploits data across 27 years spanning the period from 1990 to 2016. This is the complete sample period currently available from the ESEE, and it allows investigating the drivers and consequences of profound changes in robot diffusion over the last three decades or so. 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. 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 strata 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

\footnote{For details see https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp (accessed on Feb 19, 2019).}
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". Based on this question, 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 firms may adopt in the production process and generate indicators for CAM, CAD and FLEX, as further controls in our analysis (more on this below). 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.

Before describing further variables we use in our empirical analysis, we document some patterns of robot use across time and industries.

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

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 grey lines consider, respectively, large firms (those with more than 200 employees) and small firms (those with up to 200 employees).

Figure 2 depicts the evolution of robot diffusion in the Spanish manufacturing sector over the period 1990-2014. The left panel shows that just about 8% of all firms were using robots in their production process in 1990. This share has grown considerably over time, to roughly 22% 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). First, in 1990 already one

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7 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 actividad 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”.

8 CAM, CAD or FLEX are construct as 0/1 indicator variables equal to one if the firm uses computer-digital machine tools (CAM), computer-assisted design (CAD), or, combination of some of the above systems through a central computer, e.g. CAM, flexible manufacturing systems, etc. (FLEX). We do not use information on Local Area Network adoption as a further indicator since information on LAN adoption is only available from 2002 onwards.

9 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.
third of large firms had adopted robots in their production, while the same number for small firms was just 6%. Secondly, the absolute difference between these shares has grown over time, such that in 2014 about 60% among large firms use robots vs. 20% among small firms. The right panel of the figure shows the evolution of employment shares corresponding to robot firms. In 2014, almost 50% of all workers in Spanish manufacturing were employed in firms using robots, while the same number was more than 70% (37%) when only considering employment in large (small) firms. Taking stock, robot firms represent now a significant part of Spanish manufacturing, especially among the large businesses, and it therefore seems important to shed more light on the motives behind robot adoption along with the effects of this technology on production and employment.

Figure 3: Share of robot firms by industry (1990 vs. 2014)

Notes: The figure shows the share of robot firms by industry. Black bars show data for 1990 and gray bars for 2014.

Our data also reveal a high degree of heterogeneity in robot diffusion and robot adoption rates across industries. Figure 3 depicts the share of firms 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 (57%), Furniture (31%), and Plastic & Rubber Products (30%). 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. Not all industries are adopting robots at the same pace and magnitude.

We now continue by describing in more detail our data-set and the variables we employ in our empirical analysis. Since we are interested in the effects of robot adoption (i.e., firms switching from non-robot use to first-time robot use in production), we restrict our sample to firms that do not use robots in the first year they appear in our data. Moreover, we drop sample observations after a firm undergoes a major restructuring due to changes in corporate structure (e.g. following a

\footnote{Recall that firms always report whether or not they use robots in the year of sample entry.}
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. 646 (15%) of these firms adopt robots at some point during the sample period (“robot adopters”) and 3,800 (85%) never adopt robots (“non-adopters”). Furthermore, 62% among robot adopters keep on using robots throughout, while 30% report the use of robots for a certain period of time and abandon them afterwards. Finally, less than 10% of robot adopters switch back and forth several times. For our purposes, it is unclear how to interpret these multiple switches and we therefore drop these firms from our analysis.

In our empirical analysis, we employ a rich array of firm-specific variables. These include output, labor productivity, employment (total, manufacturing and by skill level), average wage, labor cost share, capital intensity, R&D intensity, skill intensity, export status, import status, and firm’s ownership structure (foreign vs. domestic). Output is given by the market value of the firm’s total annual production.\(^{11}\) Labor productivity is defined as value added per worker. Employment measures are total employment, given by the average number of workers during the year, and manufacturing employment, given by the number of workers at the firm’s industrial as opposed to non-industrial establishments. Based on this information, we also compute the share of manufacturing employment at the firm level. The average wage is constructed as total labor costs (gross salaries and wages, compensations, social security contributions paid by the company) divided by total employment. The labor cost share is calculated as labor costs divided by output. Moreover, we use direct firm-level information on the workforce composition by education to compute measures of the firm’s skill intensity. We know the numbers of workers with a Master’s degree (five-year university degree), a Bachelor’s degree (three-year university degree), and no university degree. Capital intensity is the value of the firm’s capital stock divided by effective work-hours. R&D intensity is the ratio of total expenses in R&D over total sales. Exporter and importer status dummies are equal to one if the firm reports positive export or import values, respectively. Foreign ownership indicates whether the firm is in foreign or domestic ownership (applying a threshold for foreign-owned capital of 50%). All variables are available on a yearly basis, except for the information on workers’ education levels, which are available every four years.

In Table 1 we present descriptive statistics on variables we employ throughout the empirical analysis. Here we pool the data across all years and then sort observations into groups of firms that never use robots in our sample and firms that adopt robots at some point in time. We find differences between the two groups in terms of output. Furthermore, firms using robots have consistently higher employment levels in total (even among all skill groups) as well as in manufacturing establishments, while there seems to be no clear difference in the share of manufacturing employment between robot and non-robot firms. On the cost side, robot firms tend to have higher wages but lower labor costs shares. Significant variation in globalization variables between the two groups is also of a great

\(^{11}\)Remember, this variable as well as all other value variables are expressed in constant 2006 prices using firm-level price indices. Thus, changes in our output measure over time within a firm reflect changes in physical output, rather than changes in prices (see Ornaghi, 2006)
Table 1: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Robot adopters (1)</th>
<th>Non-adopters (2)</th>
<th>Observations (1)/(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output (in logs)</td>
<td>15.973</td>
<td>14.407</td>
<td>7,547/25,169</td>
</tr>
<tr>
<td></td>
<td>(2.482)</td>
<td>(3.049)</td>
<td></td>
</tr>
<tr>
<td>Labor productivity (in logs)</td>
<td>10.552</td>
<td>10.316</td>
<td>7,382/24,010</td>
</tr>
<tr>
<td></td>
<td>(0.650)</td>
<td>(0.673)</td>
<td></td>
</tr>
<tr>
<td>Total employment (in logs)</td>
<td>4.475</td>
<td>3.510</td>
<td>7,501/24,578</td>
</tr>
<tr>
<td></td>
<td>(1.368)</td>
<td>(1.187)</td>
<td></td>
</tr>
<tr>
<td>Manufacturing employment</td>
<td>4.421</td>
<td>3.461</td>
<td>7,361/24,138</td>
</tr>
<tr>
<td>(in logs)</td>
<td>(1.344)</td>
<td>(1.163)</td>
<td></td>
</tr>
<tr>
<td>Share of manufacturing</td>
<td>0.961</td>
<td>0.964</td>
<td>7,367/24,151</td>
</tr>
<tr>
<td>employment</td>
<td>(0.129)</td>
<td>(0.118)</td>
<td></td>
</tr>
<tr>
<td># low-skilled workers (in logs)</td>
<td>4.386</td>
<td>3.460</td>
<td>2,370/9,264</td>
</tr>
<tr>
<td></td>
<td>(1.342)</td>
<td>(1.155)</td>
<td></td>
</tr>
<tr>
<td># high-skilled workers</td>
<td>1.871</td>
<td>1.274</td>
<td>1,761/4,881</td>
</tr>
<tr>
<td>(in logs)</td>
<td>(1.345)</td>
<td>(1.241)</td>
<td></td>
</tr>
<tr>
<td>Average wage (in logs)</td>
<td>10.136</td>
<td>9.967</td>
<td>7,420/24,187</td>
</tr>
<tr>
<td></td>
<td>(0.447)</td>
<td>(0.488)</td>
<td></td>
</tr>
<tr>
<td>Labor cost share</td>
<td>0.285</td>
<td>0.342</td>
<td>7,447/24,127</td>
</tr>
<tr>
<td></td>
<td>(0.214)</td>
<td>(0.476)</td>
<td></td>
</tr>
<tr>
<td>Capital intensity (in logs)</td>
<td>3.432</td>
<td>2.852</td>
<td>7,081/23,176</td>
</tr>
<tr>
<td></td>
<td>(0.987)</td>
<td>(1.147)</td>
<td></td>
</tr>
<tr>
<td>Skill intensity (in logs)</td>
<td>0.051</td>
<td>0.043</td>
<td>2,392/9,371</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.069)</td>
<td></td>
</tr>
<tr>
<td>R&amp;D intensity (in logs)</td>
<td>0.343</td>
<td>0.189</td>
<td>7,444/24,564</td>
</tr>
<tr>
<td></td>
<td>(0.618)</td>
<td>(0.495)</td>
<td></td>
</tr>
<tr>
<td>Exporter status</td>
<td>0.704</td>
<td>0.484</td>
<td>7,487/24,614</td>
</tr>
<tr>
<td></td>
<td>(0.456)</td>
<td>(0.500)</td>
<td></td>
</tr>
<tr>
<td>Importer status</td>
<td>0.692</td>
<td>0.473</td>
<td>7,470/24,358</td>
</tr>
<tr>
<td></td>
<td>(0.462)</td>
<td>(0.499)</td>
<td></td>
</tr>
<tr>
<td>Foreign owned</td>
<td>0.155</td>
<td>0.081</td>
<td>7,523/24,697</td>
</tr>
<tr>
<td></td>
<td>(0.392)</td>
<td>(0.272)</td>
<td></td>
</tr>
</tbody>
</table>

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 industrial as opposed to non-industrial establishments. Share of manufacturing employment is the number of workers employed at industrial establishments divided by the total number of workers employed by the firm. Low-skilled workers are defined as workers with a three-year university degree or less. High-skilled workers are defined as workers with a five-year university degree. Average wage is computed as labor costs divided by total employment. Labor cost share is labor costs divided by the total production value. Capital intensity is the value of the firm’s capital stock divided by effective work-hours. Skill intensity is the share of workers with Master’s degree in total employment. R&D intensity is the ratio of total expenses in R&D over total sales volume. We add one to all factor intensity variables 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%.

interest. There are much more exporters and importers among robot firms in comparison to their peers who do not adopt robots at all. Further, a greater proportion of robot firms is foreign owned. Of course, these differences may be caused by factors unrelated to the adoption of robots. Sorting out differences arising from a pure selection effect and establishing causality is one of the main goals.
in our empirical analysis.

3 A theoretical perspective on firm-level robot adoption

This section provides a theoretical underpinning for our empirical analysis. 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 discussion to derive hypotheses about the robot adoption decision of firms, as well as about the implications of robot adoption for output, labor costs, and labor demand, and aggregate industry productivity.

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

\[
q(\omega) = Ap(\omega)^{-\frac{1}{1-\beta}},
\]

where \( \beta \) controls the (constant) elasticity of substitution \( 1/(1 - \beta) > 1 \) between any two varieties and \( A \) is a demand shifter.\(^{12}\) As for the production side, we follow Acemoglu and Restrepo (2018b) in writing output as a composite of different tasks combined in a constant elasticity of substitution (CES) aggregate. In contrast, we adopt a firm-level view where, similar to Melitz (2003), 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 \( \omega \) is given by

\[
x(\omega) = \phi(\omega) \left( \int_{N(\omega)-1}^{N(\omega)} x(\omega, i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}},
\]

where \( \sigma \) denotes the elasticity of substitution between tasks, \( x(\omega, i) \) denotes the output of task \( i \) in firm \( \omega \) and \( N(\omega) \) determines the type of tasks the firm has to perform. Note that our measure of tasks is normalized to one and sets the limits of integration to \( N(\omega) - 1 \) and \( N(\omega) \), where \( N(\omega) \) is given exogenously, and we allow \( N(\omega) \) to vary across firms.\(^{13}\) An increase in \( N(\omega) \) 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 \( i > I \) can only be performed by human labor. The parameter \( I \in [N(\omega) - 1, N(\omega)] \)

\(^{12}\)As is well known, the demand function in Eq. (1) with \( A = EP^{\frac{1}{1-\beta}} \) and \( P = \left[ \int_{\omega \in \Omega} p(\omega)^{\frac{1}{1-\beta}} d\omega \right]^{-\frac{1-\beta}{\beta}} \) 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 \( \Omega \).

\(^{13}\)Capuano et al. (2017) provide evidence for substantial heterogeneity in the type of tasks across plants within industries in Germany. Most of the results we develop during the subsequent analysis do not depend on this second type of heterogeneity. However, it allows us to easily capture differences in skill intensity among firms in an extension to this baseline framework. More on this below and the Supplement to this paper.
thus reflects the ability level of robots in performing tasks, i.e. the capability of doing different tasks simultaneously. This parameter is of course likely to vary across industries and time. Specifically, we have

\[ \bar{c}(\omega, i) = \mathbb{1}[i \leq I] \eta(i)k(\omega, i) + \gamma(i)l(\omega, i), \]

(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 \( i \). 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, 2018a).\(^{14}\)

As in Acemoglu and Restrepo (2018a), 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 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 unit production costs of a firm automating the production process for all tasks \( i \leq I \) as

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

(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 efficiency over all tasks performed by robots and labor, accordingly.\(^{15}\) The superscript \( a \) indicates that the production process has been automated. However, this decision is endogenous and requires the payment of a fixed cost, denoted \( F^a > 0 \). Not paying the fixed cost means that the firm has to perform all tasks using human labor with corresponding unit cost of \( c(\phi(\omega), N(\omega), N(\omega) - 1) = \frac{1}{\phi(\omega)} \left[ \gamma(N(\omega), N(\omega) - 1)w^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \).

Using constant mark-up pricing, a firm’s profit gain from robot adoption, defined as \( \Delta \pi(\omega) \equiv \)
\( \pi(a) - \pi(\omega) \), is given by\(^ {16}\)

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

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

\[
\kappa(N(\omega), I) \equiv \left( \int_{N(\omega)-1}^{N(\omega)} \gamma(i)\sigma-1\,di \right) ^{1/\sigma} w^{1-\sigma} + \left( \int_{N(\omega)-1}^{N(\omega)} \gamma(i)\sigma-1\,di \right) ^{1/\sigma} w^{1-\sigma} . \tag{6}
\]

Thereby, \( \kappa(\cdot) \geq 1 \) depends on the ratio of production costs with robots compared to a situation where labor is performing all tasks and thus reflects the marginal-cost savings from robot adoption. Notably, if firms perform all tasks with labor, i.e. \( I = N(\omega) - 1 \), cost savings vanish and we have \( \kappa(N(\omega) - 1, N(\omega)) = 1 \), from inspection of Eq. (6). Given our assumptions on the comparative advantage of labor in more complex tasks and lower effective robot capital costs for all automatable tasks \( (\tau/\eta(I) < w/\gamma(I)) \), we can furthermore conclude that \( \kappa(\cdot) \) ceteris paribus (that is for given \( N(\omega) \)) increases in the share of automatable tasks \( I \), while it decreases in the complexity of tasks \( N(\omega) \) (for given \( I \)). Taking stock, the decision to adopt robots implies a simple trade-off between low variable costs coupled with high fixed costs in the case of automated production vs. low fixed costs coupled with high variable costs in the case of non-automated production.\(^ {17}\)

### 3.1 Selection and treatment effects of robot adoption

Having specified our framework, we are now equipped to investigate the selection of firms into robot adoption and its implications on output, labor costs, and labor demand, and aggregate industry productivity.\(^ {18}\) For \( \kappa(\cdot) > 1 \) the profit gain from robot adoption in Eq. (5) is increasing in a firm’s baseline productivity \( \phi(\omega) \). As standard in the literature this allows us to define a cut-off productivity level \( \phi'(\omega) \) at which a firm is indifferent between adopting and not adopting robots for a given task range \( N(\omega) \), defined by \( \Delta \pi(\omega) |_{\phi(\omega) = \phi'(\omega)} = 0 \). Hence, comparing two firms with similar task ranges, ex-ante more productive firms are more likely to adopt robots in production. Over

\(^{16}\)Note that profits for a firm \( \omega \) using robots can be written as \( \pi^a(\omega) = (1 - \beta) A \left[ \frac{1}{\beta \phi(\omega)} \right] ^{-\frac{1}{1-\sigma}} w^{1-\sigma} - F^a - F \) while profits for the same firm but using no robots are given by \( \pi(\omega) = (1 - \beta) A \left[ \frac{1}{\beta \phi(\omega)} \right] ^{-\frac{1}{1-\sigma}} w^{1-\sigma} + F^a - F \), where \( F \) denotes overall fixed costs of production. Computing the difference among the two and using the definition of \( \kappa(\cdot) \) in Eq. (6) gives Eq. (5).

\(^{17}\)In our framework, this trade-off seems to be unnecessarily complicated, by using a CES production technology and allowing firms to differ in several dimensions. However, when modeling automation we aim to depart from an approach that is used in recent contributions (e.g. Acemoglu and Restrepo, 2018a) thereby highlighting that we end up in a situation that is well established in the literature. For instance, the subsequent results are similar to mechanisms described in Yeaple (2005) and Bustos (2011) who highlight how trade liberalization affects technology upgrading, or in Egger et al. (2015) and Groizard et al. (2014) who model offshoring as reducing variable production costs due to substitution of domestic labor with cheap foreign labor (see also the discussion in the introduction).

\(^{18}\)In the interest of space and readability, we provide analytical details to the subsequent results in the Supplement to this paper.
time, the cut-off productivity is likely to decrease, if fixed costs for robot adoption \((F^a)\) decline or the capability of robots doing different tasks simultaneously \((I)\) increase. Furthermore, drawing from an extensive literature building on Melitz (2003), this affects the composition of firms within industries. As ex-ante more productive firms gain market share 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 raises the exit rates of non-robot firms and reduces their output and employment.

In a first extension suppose firms can choose to serve consumers in a foreign country. This country is fully symmetric to the domestic economy but exporting requires the payment of a fixed export and per-unit iceberg type transport costs, denoted by \(F^x\) and \(\tau\), respectively. As it is a well established fact in the literature, the introduction of fixed export costs generates (sharp) selection of ex-ante more productive producers into exporting. Due to symmetry among the two countries, operating profits of exporting firms are now scaled by a constant factor \(1 + \tau^{-\beta/(1-\beta)}\). This setting is not to different to Bustos (2011) and we can conclude that exporters have a higher incentive to adopt robots as the gains from investments – the reduction in variable production costs – can be scaled up to a larger customer base in home and foreign.

In a second extension assume that firms can use two type of skills, low-skilled and high-skilled workers, indicated by lower script \(l\) and \(h\), accordingly. Following Acemoglu and Autor (2011), it is plausible to assume that high-skilled workers have a comparative advantage over their low-skilled coworkers in the performance of more complex tasks. This could be simply reflected in our model by assuming that the ratio of labor efficiency for the two skill types, i.e. \(\gamma_h(i)/\gamma_l(i)\) is strictly increasing in \(i\). In such an environment firms will not only compare the production costs of robots and human capital across tasks but also compare the effective labor costs in each task among the two skill types, that is \(w_l/\gamma_l(i)\) to \(w_h/\gamma_h(i)\). Given that high-skilled workers have a relative advantage in performing more complex tasks this results in a cut-off task, at which firms are indifferent in hiring high-skilled or low-skilled workers for the performance of that task. Comparing two firms with similar productivity but different task complexity, we can thus state that a firm with higher \(N(\omega)\), would have a higher skill intensity. However, the analysis above also revealed that firm’s with higher task complexity are less likely to adopt robots, since they substitute human capital for a smaller task range. Thus, using the modification with two skill types, we can draw the conclusion that firms with a lower skill-intensity are more likely to adopt robots.\(^{19}\)

Finally, we now proceed and use our framework to generate insights on the effects of robot adoption on firm-level outcomes such as output, labor costs, and labor demand. First of all, by imposing a comparative advantage of robots in the production of automatable tasks, it is straightforward to conclude that robot adoption raises firm output. Additionally, due to our assumptions on the task production function specified in Eq. (3), it follows immediately that robot adoption reduces the labor cost share, as robots substitute human capital in automated tasks. However, the overall

\(^{19}\)The motivation for this extension is given by the fact that we do not observe tasks, and thus task complexity in the ESEE data-set. However, following the extension, we can proxy task-complexity by the skill composition of firms in the subsequent empirical analysis.
impact of automation on labor demand within firms is less clear cut. Precisely, it depends on two opposing effects: on the one hand, the displacement effect reduces demand for workers as part of the workforce is substituted by robots. On the other hand, the productivity effect refers to the fact that robot adoption raises the efficiency in production and thus output and employment within these firms. Similar to the discussion in the offshoring literature (see Grossman and Rossi-Hansberg, 2008), the productivity gains may be strong enough to outweigh the losses. Thereby, the strength of the displacement effect depends on the share of automatable tasks, and thus the parameters $I$ (in combination with $N(\omega)$), while the size of the productivity effect depends on the realized variable cost savings from robot adoption, determined by the efficiency parameters for robots and workers, $\eta(i)$ and $\gamma(i)$, respectively, and factor prices. Finally, a natural question is which type of skills (and thus workers) are specifically affected by automation. Using the extension on two skill types from above, we can state that low-skilled workers are much more likely to be affected by automation, since they perform less complex tasks which are more likely to be automated. However, as long as not all low-skilled workers are fully substituted by robots, the productivity effect is also at work for this skill type.\(^{20}\)

4 Which firms adopt robots?

We begin our empirical analysis by investigating which firm-specific characteristics influence the decision to adopt robots. A large literature inspired by the work of Joseph Schumpeter explores market-specific characteristics that influence rates of technological innovation, adoption, and diffusion. In contrast to this literature, we focus on firm-specific characteristics, in order to take full advantage of the detailed firm-level information available in the ESEE data-set.

Our theoretical discussion includes a first set of predictions that we now bring to our Spanish firm-level data. The most important prediction concerns the relationship between the likelihood of robot adoption and the productivity and size of the firm. The prediction is consistent with arguments in the literature that more efficient firms benefit more from the adoption of higher levels of technology so that we should expect to find more productive firms to be more likely to adopt robots in their production (positive selection). Identifying whether positive selection is indeed 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.\(^{21}\)

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 4 plots the distribution of base year output (deflated and in logs) for robot adopters vs. non-adopters,
Figure 4: Distribution of base year output for robot adopters vs. non-adopters

Notes: In the left (right) panel the dashed red line shows the empirical probability density function of base year output (labor productivity) 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 (labor productivity) 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. The base year labor productivity is given by the log of (deflated) value added per worker demeaned by industry.

i.e., for firms that have adopted robots four years after they first appear in the sample vs. firms that 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 industry mean, differences in firm size across industries are not driving this observation. 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 to Figure 4.\(^{22}\)

We now proceed by investigating robot adoption through the use of regression analysis. Specifically, we adopt the following basic empirical framework to describe the decision of firms to adopt robots:

$$\text{Robots}_{it} = \beta \phi_{it-1} + \gamma \mathbf{F}_{it-1} + \delta \mathbf{G}_{it-1} + \mu_{st} + \epsilon_{it}, \tag{7}$$

where the dependent variable is a 0/1 indicator variable for robot use in the production process of firm $i$ at time $t$, and where we focus on different sets of explanatory variables: (1) a firm-specific productivity variable $\phi_{it-1}$; (2) a vector of factor intensity variables $\mathbf{F}_{it-1}$; and (3) a vector of globalization variables $\mathbf{G}_{it-1}$ (with corresponding parameters to be estimated collected in $\beta$, $\gamma$, and $\delta$, respectively). We also include industry-year fixed effects given by $\mu_{st}$, in order to control for industry-specific factors determining the likelihood of robot adoption such as the degree of competition. These fixed effects 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.

\(^{22}\)When carrying out this exercise for individual industries (results not reported), we find that positive selection based on output and productivity is clearly dominating the picture. However, there are also a few industries where the data suggest no selection or even negative selection. Exploring this cross-industry heterogeneity in more detail is beyond the scope of our paper.
over time. Finally, \( \varepsilon_{it} \) is the error term. The firm’s productivity is measured as the log of labor productivity given by the firm’s value added per worker (deflated). The factor intensity variables we use are the firm’s capital intensity, skill intensity, and R&D intensity (all in logs). The globalization variables we use are 0/1 indicator variables for whether the firm is an exporter, an importer, and a foreign-owned firm, respectively.

Table 2: Robot adoption I: Cross-sectional and panel specification

<table>
<thead>
<tr>
<th>PANEL A: Cross-sectional specification</th>
<th>Robot adoption (0/1 indicator)</th>
<th>(1a)</th>
<th>(2a)</th>
<th>(3a)</th>
<th>(4a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base year labor productivity</td>
<td>0.0384***</td>
<td>0.0147</td>
<td>0.0150</td>
<td>0.00285</td>
<td></td>
</tr>
<tr>
<td>base year skill intensity</td>
<td>-0.330***</td>
<td>-0.398***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>base year exporter status</td>
<td>0.0716***</td>
<td>0.0580***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4053</td>
<td>3488</td>
<td>3986</td>
<td>3443</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.110</td>
<td>0.151</td>
<td>0.130</td>
<td>0.161</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PANEL B: Panel specification</th>
<th>Robot adoption (0/1 indicator)</th>
<th>(1b)</th>
<th>(2b)</th>
<th>(3b)</th>
<th>(4b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged labor productivity</td>
<td>0.0392***</td>
<td>0.0173***</td>
<td>0.0209***</td>
<td>0.00856</td>
<td></td>
</tr>
<tr>
<td>Lagged skill intensity</td>
<td>-0.103*</td>
<td>-0.148**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged exporter status</td>
<td>0.0345***</td>
<td>0.0253***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>7368</td>
<td>6934</td>
<td>7300</td>
<td>6879</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.039</td>
<td>0.053</td>
<td>0.052</td>
<td>0.059</td>
<td></td>
</tr>
<tr>
<td>Industry(-base)-year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Factor intensity controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Globalization controls</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
</tbody>
</table>

Notes: In Panel A 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, while in Panel B it is equal to one if the firm uses robots in a specific year and zero otherwise. 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). Exporter status is a dummy variable for positive exports. All estimates in Panel A (B) include industry-base-year (industry-year) fixed effects. Factor intensity controls are a firm’s capital intensity, defined as the firm’s deflated capital stock per worker, and R&D intensity as the firm’s deflated R&D expenditures relative to its deflated total sales (both in logs). Globalization controls are importer status, defined as a dummy variable for positive imports, and a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). We add one to all factor intensity variables before taking logs in order to keep zero observations. In Panel A all explanatory variables are measured in the base year defined as the first year the firm appears in the sample. In Panel B all explanatory variables are lagged by one year. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Moreover, in Panel B we condition on the firm not using robots in the previous year (or the most recent year for which robot data are available for that firm). Robust standard errors are given in parentheses. ***,*** denote significance at the 10%, 5%, 1% levels, respectively.

In addition to applying this empirical framework to our panel data-set, we consider a simplified version of Eq. (7) and collapse the data into a single cross-section measuring all explanatory variables in the base year (i.e., in the first year the firm appears in the sample). The dependent variable is equal to one if the firm adopts robots at some point in time during our sample period, and zero otherwise. Note that firms using robots already in the year of sample entry are excluded from the analysis. Table 2 presents OLS estimates of the simplified (cross-sectional) version of Eq. (7) in Panel A and the panel version in Panel B. Standard errors are robust to arbitrary
forms of heteroskedasticity. In column (1) we use the most parsimonious specification including productivity as the only explanatory variable alongside industry-year fixed effects. Our estimates provide evidence that the more productive firms are significantly more likely to adopt robots. This is in line with our previous observation that the output and productivity distributions of robot adopters dominate those of non-adopters already before first-time adoption. The estimated coefficient is equal to +0.038 in the cross-section and implies that an increase by one standard deviation in the firm’s base year labor productivity raises its probability of subsequently adopting robots by 2.5 percentage points.

In columns (2) and (3) we augment the specification to include factor intensity and globalization variables, respectively. We report estimates on the skill intensity and export variable, which are at the focus in our theoretical perspective on robot adoption, while we include capital- and R&D intensity as further factor controls and an import and foreign ownership indicator as globalization controls. Including these variables renders the effect of labor productivity insignificant, which reflects significant pairwise correlations among these variables. Interestingly, 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. The coefficient of export is positive and significant. These results are upheld in column (4) where we include all variables simultaneously. The estimated coefficients in the last column (4a) imply that exporting makes firms 6 percentage points more likely to adopt robots later on (controlling for productivity, 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.

By extending the analysis to estimate the panel version of Eq. (7), we find a picture that largely resembles our cross-sectional estimates, as becomes evident from Panel B. As before, the sample we use in Panel B to Table 2 includes only firms that do not use robots in the first year they appear in our data-set. We restrict attention to observations of those firms that never adopt robots as well as those that adopt robots for the first time during the sample period. Since we are interested in first time robot adoption, once a firm decides to use robots in the production process, we exclude subsequent observations from the estimation sample. Again, we find that more productive firms are more likely to become first-time robot adopters. A firm’s skill intensity contributes negatively, while the firm’s export status enters the equation positively and significantly.

In the interest of space we restrict our attention to OLS estimates in the text. Appendix A.2 reports estimates obtained with the non-linear Probit model, again for the cross-section and the panel version. The results we obtain with this alternative model are very similar to the OLS estimates. Tables A.1 report Probit estimates for the cross-sectional and the panel specification in Panel A and B, respectively.

To further understand what motivates firms to install robots in the production process, we also use firm output instead of labor productivity in estimates of Eq. (7). The results we report in Table
3 provide evidence that output is a strong and significant predictor of subsequent robot adoption. The magnitude of the effect is sizable. The estimated coefficient of +0.0483 in the cross-sectional specification without controls (see column 1a) implies that an increase by one standard deviation in the firm’s base year output raises its probability of adopting robots later on by as much as 8 percentage points. The effect remains economically meaningful, standing at 6 percentage points, after controlling for the firm’s factor intensities and globalization variables. What is interesting is that the globalization variables are rendered insignificant (at least in the panel specification in columns 3b and 4b) when using firm output instead of labor productivity. 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.\(^{23}\)

Finally, in another set of estimates we allow for non-linearity and non-monotonicity in the effects of productivity and output on robot adoption; see Tables A.3 and A.4 in the appendix for results based on the cross-section and the panel, respectively. We do this by replacing the productivity/output variable with dummy variables for each productivity/output quartile. The results are striking and indicate that firms in the top quartile of the productivity/output distribution have the highest probability of adopting robots. For example, firms in the top quartile of the output distribution are 15 percentage points more likely than firms in the bottom quartile to subsequently adopt robots even after controlling for factor intensity and globalization variables; see column (4) in Table A.3.

5 Firm-level effects of robot adoption

Having established novel facts on the selection of firms into robot adoption, we now aim to investigate potential treatment effects. In a first step, we analyze physical output adjustments arising from using robots in the production process. In a second step, we proceed and analyze employment effects, overall, for manufacturing workers and for specific skill groups, and, finally cost effects reflected in average wages and labor cost shares.

5.1 Output effects

As for the selection analysis, we begin with providing some graphical evidence on the evolution of output among the group of robot and non-robot firms. Figure 5 plots the distribution of output (deflated and in logs) and allows for a before-after comparison. To be more specific, in the left panel we look at 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 right panel provides the same comparison, now for firms that do not install robots in their production process. The figure reveals that robot adopters clearly experience a positive shift in their physical output, that is the scale of

\(^{23}\) Again, we relegate the reporting of estimates obtained with the non-linear Probit model to the Appendix A.2. For the cross-section and the panel version, the results we obtain with this alternative model are very similar to the OLS estimates; see Table A.2.
Table 3: Robot adoption II: Cross-sectional and panel specification

<table>
<thead>
<tr>
<th>PANEL A: Cross-sectional specification</th>
<th>Robot adoption (0/1 indicator)</th>
<th>(1a)</th>
<th>(2a)</th>
<th>(3a)</th>
<th>(4a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base year output</td>
<td>0.0483*** (0.00405)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base year skill intensity</td>
<td>-0.408*** (0.0996)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base year exporter status</td>
<td>0.0374*** (0.0143)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<table>
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<th>PANEL B: Panel specification</th>
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<th>(1b)</th>
<th>(2b)</th>
<th>(3b)</th>
<th>(4b)</th>
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<tr>
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<tr>
<td>Lagged exporter status</td>
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<td>Globalization controls</td>
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<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
</tbody>
</table>

Notes: In Panel A 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, while in Panel B it is equal to one if the firm uses robots in a specific year and zero otherwise. Output is the firm’s deflated output value (in logs). Skill intensity is the firm’s share of workers with a five-year university degree (in logs). Exporter status is a dummy variable for positive exports. All estimates in Panel A (B) include industry-base-year (industry-year) fixed effects. Factor intensity controls are a firm’s capital intensity, defined as the firm’s deflated capital stock per worker, and R&D intensity as the firm’s deflated R&D expenditures relative to its deflated total sales (both in logs). Globalization controls are importer status, defined as a dummy variable for positive imports, and a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). We add one to all factor intensity variables before taking logs in order to keep zero observations. In Panel A all explanatory variables are measured in the base year defined as the first year the firm appears in the sample. In Panel B all explanatory variables are lagged by one year. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Moreover, in Panel B we condition on the firm not using robots in the previous year (or the most recent year for which robot data are available for that firm). Robust standard errors are given in parentheses. *, **, *** denote significance at the 10%, 5%, 1% levels, respectively.

Operation, since the distribution of output once robots are installed (blue line), clearly dominates the distribution of output before the robot adoption (dashed red line). Contrary, for the group of non-robot adopters, both distributions are almost identical.

To identify a causal effect of robot adoption on the output of firms we estimate the following equation:

\[
\text{Output}_{it} = \gamma_1 \text{Robots}_{it-4} + \gamma_2 \text{Robots}_{it-4} + \beta \mathbf{X}_{it-4} + \mu_i + \mu_{st} + \varepsilon_{it},
\]

where the dependent variable \(y_{it}\) denotes (log) deflated output of firm \(i\) in year \(t\), \(\mathbf{X}_{it-4}\) is a vector of time-varying firm-level controls, that are lagged by four periods, with the corresponding vector of parameters \(\beta\) to be estimated, \(\mu_i\) and \(\mu_{st}\) are a firm and industry-year fixed effect, respectively, and \(\varepsilon_{it}\) is an error term with zero-conditional mean.\(^{24}\) Notably, \(\mu_{st}\) controls for general time trends and

\(^{24}\)Using one year lagged instead of four year lagged controls, does not alter our estimates. However, we prefer to
industry shocks affecting firms equally within one of the 20 different manufacturing industries. The parameters of interest in (8) are $\gamma_1$ and $\gamma_2$, both capturing the impact of robot adoption on firm output. These parameters indicate a percentage point change in output if a firm adopted robots in their production process (in $t$ or accordingly $t-4$).

By including firm-fixed affects, adjustments in output are identified through within-firm variation in robot adoption. They furthermore control for selection based on time-invariant components, like a firm’s baseline productivity, akin to $\phi(\omega)$ in our theoretical framework. However, in the previous section we have documented that selection into robot adoption also depends on other, especially time-varying factors. We therefore include a set of firm-year specific controls in the vector $X_{it-4}$ that turned out to be statistically significant predictors of robot adoption (see Section 4). Specifically, we use labor productivity, capital-, skill- and R&D-intensity (all in logs) and indicator variables for exporter, importer and foreign. We also include our robot indicator for the following period ($\text{Robot}_{t+4}$), to control if firms experience positive output effects already before the robot adoption. Finally, we also make use of a propensity score reweighting estimator, that tackles the selection into robot adoption.

To be more specific, we use propensity scores to reweigh each firm-year observation in (8) by its probability to adopt robots. The treatment group represents those firms once they adopted robots, while we include those firms that never adopt robots into the control group. The propensity scores are obtained by running probit regressions of robot adoption (treatment) on sales and sales growth, labor productivity and its growth rate, capital-, skill- and R&D-intensity, indicators for exporter, importer and foreign ownership and year fixed effects. Hence, we use the same set of variables, that turned out to be important economic determinants for the selection into robot adoption. However, in the previous section we have documented that selection into robot adoption also depends on other, especially time-varying factors. We therefore include a set of firm-year specific controls in the vector $X_{it-4}$ that turned out to be statistically significant predictors of robot adoption (see Section 4). Specifically, we use labor productivity, capital-, skill- and R&D-intensity (all in logs) and indicator variables for exporter, importer and foreign. We also include our robot indicator for the following period ($\text{Robot}_{t+4}$), to control if firms experience positive output effects already before the robot adoption. Finally, we also make use of a propensity score reweighting estimator, that tackles the selection into robot adoption.

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Notes: The left panel depicts a before-after comparison 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 of these firms at time $t$ and at time $t+4$, respectively. The right panel repeats the corresponding comparison of 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.
Additionally, we also use the growth rate of labor productivity and sales, to control for recent performance differences among firms. By including observable time-varying firm characteristics, we hope to also match the distribution of important unobservable characteristics, that affect the decision to install robots in the production process. As it is standard in the literature, we use the estimated propensity score \( \hat{p} \) and reweight treated firms by \( 1/\hat{p} \) and firms within the control group by \( 1/(1-\hat{p}) \).

Table 4: Output effects of robot adoption

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tr>
<td>( Robots_t )</td>
<td>0.157***</td>
<td>0.106***</td>
<td>0.162***</td>
<td>0.120***</td>
<td>0.126***</td>
<td>0.119**</td>
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<td></td>
<td>(0.0289)</td>
<td>(0.0344)</td>
<td>(0.0315)</td>
<td>(0.0370)</td>
<td>(0.0385)</td>
<td>(0.0495)</td>
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<tr>
<td>( Robots_{t-4} )</td>
<td>0.121***</td>
<td>0.126***</td>
<td>0.119***</td>
<td>0.111**</td>
<td>0.121***</td>
<td>0.0815</td>
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<tr>
<td></td>
<td>(0.0325)</td>
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<td>(0.0337)</td>
<td>(0.0468)</td>
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<td>(0.0545)</td>
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<tr>
<td>( Robots_{t+4} )</td>
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<td>0.0724</td>
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<td>Yes</td>
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<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: Robots is a 0/1 indicator variable equal to one if the firm uses robots in a period \( t \). The dependent variable in all columns is a logarithm of real output. Selection controls (in \( t-4 \)) are firm’s deflated labor productivity (in logs), firm’s deflated capital intensity (in logs), firm’s deflated skill intensity (in logs), firm’s deflated R&D intensity (in logs), exporter, importer and foreign ownership status. 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. Clustered standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table 4 shows the results of estimating Eq. (8). Column (1) reports the coefficients for \( \gamma_1 \) and \( \gamma_2 \), that is percentage point changes in output due to robot adoption in \( t \) or accordingly \( t-4 \). In column (2) we also include estimates on future robot adoption (in \( t+4 \)). The coefficient is positive and not statistically different to zero, indicating that we do not properly control for selection into robot adoption in the fixed-effects estimation. Column (3) and (4) reports estimation results, now including our time-varying selection controls contained in \( X_{it-4} \), while in column (5) and (6) we apply our propensity score estimator, as described above. By controlling for firm-year specific selection determinants, the coefficient on future robot adoption is not different to zero (in a statistically sense). Overall, we find positive and sizable output effects for firms adopting robots in their production process throughout all the different specifications in the vicinity of 10 to 16 percent.

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25 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 and non-robot adopters are balanced. Output to the propensity score estimation can be found in Table A.5 in the Appendix to this paper.

26 Since we use labor productivity in \( t-4 \) as a selection control and labor productivity together with its growth rate in the propensity score estimates, we restrict our treatment analysis here to physical output of firms and delay an analysis to productivity effects of robot adoption to the subsequent section.

27 In an additional set of estimates we investigate if the documented output gains from robot adoption are stronger.
5.2 Employment effects

Having documented positive and sizable output effects, we now aim to investigate the implications of robot adoption on employment, in fact overall and for specific group of workers, and the treatment on firms’ labor costs. Building on the theoretical literature on automation we concluded that adopting robots should reduce the labor cost share, while the impact on employment is less clear cut and depends on two competing forces. One the one hand human capital is replaced by robots (displacement effect), on the other hand installing robots raises output and thus demand for human capital in non-automated tasks (productivity effect). The strength of these two forces determines whether robot adoption leads to job creation or not within firms. Finally, these employment effects might be specific to certain skill groups. That is, the productivity effect predominantly affects workers in non-automated tasks, while workers in automated tasks are especially treated by robots. To investigate this, we estimate an equation akin to Eq. (8), where we use different employment and costs measures, instead of output, as depended variable. Results are reported in Table 5. In panel A we control for time-varying determinants of robot adoption by including our selection controls. In Panel B we use our propensity score estimates. All estimates include firm and industry-year fixed effects.

From column (1) in Table 5 we see that robot adopting firms raise overall employment by around 10 percentage. On the other hand we also observe significant reductions in the share of labor costs in overall costs from column (2). Taking into account output gains documented in the previous analysis, it seems that robots replace human capital to some extend, thereby reducing a firms labor costs. However, the gains from robot adoption are clearly dominating the displacement effect, such that firms grow not only in terms of (real) output, but also in terms of employment. Are these employment affects biased towards specific skills or group of workers? In column (3) and (4) we distinguish between low-skilled and high-skilled workers. We do not find negative and statistically significant effects by looking at any of the two skill groups separately. If anything, we see positive employment effects especially for the group of low-skilled workers. That robot adoption might affect workers with varying skills differently, seems to be also neglected by looking at column (7), where we use the average wage as an outcome variable. We do not find statistically effects on average wages, as a proxy for the composition of workers within firms. Finally, in columns (5) and (6) we look at manufacturing employment and the respective share in overall employment. Again, we do not find strong effects for this group of workers. Even though manufacturing employment increases slightly, the share seems to decline, however the coefficients are not statistically different from zero.

5.3 Treatment effects of adopting alternative systems in the production process

As stated in Section 2, firms are not only asked if they use robots in their production process. Firms also report alternative systems in their production process, namely if they use computer-digital for internationalized firms. We do not find robust evidence that exporters (or importers or foreign owned firms) experience stronger output gains from adopting robots.
machine tools (CAM), computer-assisted design (CAD), or, combination of some of the systems through a central computer, e.g. CAM, flexible manufacturing systems, etc. (FLEX).\textsuperscript{28} We use this information to investigate if there are differences between robot adoption and these alternative technological investments in the production process and, if including them in our analysis as further control variables affects the estimates on robot adoption on output and employment. In the interest of readability and to save on space we briefly summarize the main finding from this exercise here, while reporting detailed regression output in the Supplement in Section S.2. It turns out that the adoption of computer-digital machine tools or flexible manufacturing systems through a central computer raises firm output. However, in contrast to robot adoption, the estimates turn out to be less important and they also lose significance. Adopting computer-assisted designs even turns out to have no statistically significant effect on output. Including CAM, CAD and FLEX as additional controls has no impact on the significance and the size on our estimated coefficients for robot adoption. Furthermore, we find positive employment effects for the three systems, both in terms of significance and size. However, there is one important difference to robot adoption, as none of these systems reduces the labor cost share. Again, including them as additional controls has no impact on the significance and the size on our estimated coefficients for robot adoption on different employment outcomes.

6 Robot adoption and intra-industry reallocations

In the previous sections we have documented that robot adoption is much more likely in ex-ante larger and more productive firms and that adopting firms experience substantial shifts in output and employment. In this section we aim to investigate how non-adopting firms are affected from the increased robot density within their industry. Furthermore, since robot-adoption is not random, this could reinforce the heterogeneity within industries with implications on the relationship between robots and the evolution of the productivity distribution.

6.1 Increased robot exposure and its impact on non-robot adopting firms

In a first step we are interested how non-robot adopting firms are affected if more and more competitors start to automate their production process. To do so we estimate variants of the following equation:

\[
\text{Outcome}_{it} = \gamma_1 \text{Robot-density}_{st} + \gamma_2 \text{Robot-density}_{st} \times \text{Robot-use}_i + \\
\beta_1 X_{it-4} + \beta_2 X_{st} + \beta_3 X_{st} \times \text{Robot-use}_i + \mu_i + \mu_t + \epsilon_{it}. \tag{9}
\]

For the outcome variable we use employment, real output or the exit probability of firm \(i\) at time \(t\) in Panel A, B and C of Table 6, respectively. Robot-density varies across industries \(s\) and over time

\textsuperscript{28}While robots are used less frequently in the production process, there is a slightly positive correlation between robot adoption and these alternative systems.
Robot-use is a firm specific 0/1 indicator variable equal to one if the firm reports to use robots at least once throughout the sample period. Our measure for robot-density is constructed from our ESEE data and is thus limited to those years in which firms report information on the use of robots in their production process. In addition, and to get yearly variation in robot density, we make use of robot information at the industry level from the International Federation of Robotics (IFR). Specifically, we use the stock of robots over the period 1993 to 2016 available in the IFR data for different industries. In columns (1) to (3) we report estimates where robot-density is constructed from our ESEE data, in columns (4) to (6) we report estimates employing the IFR data. Estimates in all columns use firm (μ_i) and year (μ_t) fixed effects. In columns (2), (3), (5) and (6) we include our selection controls for robot adoption in the vector X_{it-4} (see Section 4). Finally, in columns (3) and (6) we also include industry-year factor controls in the vector X_{st}, namely industry-means in capital, skill and R&D intensity, and also interact those with our indicator for robot use.

From inspection of Panel A in Table 6, it becomes evident that an increase in robot density has a significant negative impact on employment in firms. Importantly, in combination with the coefficient on the interaction term between robot-density and robot-use, we find that the negative effects are limited to those firms that do not install robots in their production process. Put differently, increased robot density within industries reduces employment, but this effect is limited to those firms where they are (maybe) the least expected. Contrary, we again find positive employment effects in the group of robot users, as documented previously in Section 5. Looking at Panel B, we see similar effects if we look at output instead of employment, while effects seem to be even more pronounced if one compares the estimated coefficients reported in Panel A and B. In Panel C we finally document higher exit rates only for those firms that do not use robots if robot-density increases, which corresponds to an increase in the cut-off productivity in our theoretical framework. Interestingly, we find similar results on employment, output and exit rates if we use the stock of robots within industries from the IFR data. Even though changes in both measures reflect higher exposure to robots in industries, there is a remarkable difference. While changes in robot-density throughout columns (1) to (3) reflect adjustments in the share of firms using robots, that is the

29 Instead of using the share of sales by robot firms, we also compute robot-density as the share of firms that use robots in the total number of firms, as the share of output by firms that use robots in industry output, or as the share of employment by firms that use robots in total industry employment. Using these alternative measures does not change our results.

30 To construct meaningful measures for robot-density within industries we do not restrict the sample to firms that do not use robots in the first year they appear in the sample, when we compute the robot-density. We also use the full sample of firms in the empirical analysis. However, results do no change if we restrict the sample in the estimation to firms that do not use robots in the first year they appear in the sample, i.e. using an indicator for robot-adoption instead of robot-use.

31 Table A.6 in the Appendix provides details to the mapping between the different industry classifications in the ESEE and the IFR data.

32 Following the analysis from Section 5.3, we run an additional robustness analysis (not reported), where we also include density measures for the use of computer-digital machine tools (CAM), computer-assisted design (CAD), or, combination of some of the systems through a central computer (FLEX). This does not affect the significance of our estimates.
Taking stock, the results we presented so far confirmed the conclusions we draw from Figure 1 in the introduction. Robot adopting firms grow in employment while negative employment effects arise in those firms that do not automate their production process. Thus, there is substantial reallocation of market shares and resources among firms within industries as a result from non-random robot adoption.

6.2 Decomposing productivity gains

In a final step we now aim to investigate how robots contributed to total factor productivity gains. Thereby, we decompose the TFP gains into direct gains arising from the adoption of new technologies in form of robots and indirect gains arising from the reallocation of market shares between the less productive non-adopting firms and more productive robot-adopting firms. To do so, we first estimate total factor productivity by using a standard measure following the procedure described in Olley and Pakes (1996). Using this measure we compute the employment weighted TFP for our sample. In a next step, we estimate the impact of robot adoption on TFP, following our treatment analysis described in Section 5. Specifically, adopting the specification with selection controls, we get estimates for robot adoption in $t$ of 0.135 and in $t-4$ of 0.084, both statistically significant at the 1 percent level. These estimates are used to correct the TFP growth in robot adopting firms, which allows us to construct a counterfactual evolution eliminating firm-specific TFP gains due to robot adoption. In a last step, we use our estimates reported in Table 5 and Table 6 to adjust the employment weights for robot-adopting firms and non-adopting firms. This allows us to construct a counterfactual evolution eliminating firm-specific TFP gains due to robot adoption, as well as labor reallocations caused by firm-specific robot adoption and increasing industry-wide robot intensity. The three constructed measures are all normalized to 100 in the base year 1990. Notably, to construct meaningful measures for employment share, we restrict the analysis to a balanced sample of firms that are active between 1990 to 2016.

Figure 6 illustrates the evolution of actual TFP and our constructed counterfactual measures. By looking at the solid black line, we see that for the sample of firms TFP triples over the period of 27 years, which corresponds to a (plausible) annual growth rate of TFP of about 4%. Excluding direct and indirect TFP gains reduces the TFP gains over the sample period, such that TFP only doubles from 1990 to 2016, as revealed by the short-dashed light grey line depicting the counterfactual without technical and reallocation gains. Comparing it to the counterfactual without technical gains, we see that the differences in the employment evolution can explain about one third of the difference between the actual TFP gains and the counterfactual without direct and indirect gains, while the direct technical gains can explain about two thirds of the difference. Put differently, overall TFP gains from robot adoption can be decomposed into direct gains arising from higher efficiency in robot using firms and into indirect gains arising from growing (falling) market shares.
Figure 6: Actual vs. counterfactual evolution of aggregate TFP (1990-2016)

Notes: The figure depicts the evolution of average TFP (weighted by firm-specific employment shares) in a balanced sample of firms from 1990-2016. The solid black line depicts the actual evolution; the long-dashed dark grey line depicts the counterfactual evolution eliminating firm-specific TFP gains due to robot adoption; the short-dashed light grey line depicts the counterfactual evolution eliminating firm-specific TFP gains due to robot adoption, as well as labor reallocations caused by firm-specific robot adoption and increasing industry-wide robot intensity.

Source: Authors’ computations based on ESEE data.

for robot (non-robot) adopting firms. The former contributes by 2/3 the latter by 1/3 to overall TFP gains.

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 the last decades. We document that productivity and a less skilled workforce are significant determinants for automating the production process. Furthermore, we document compelling evidence for a fundamental complementarity between globalization and robot adoption, that is exporters are considerably more likely to adopt robots. We then consider these (and further) selection controls to control for non-random robot adoption. Specifically, we combine a difference-in-difference approach with a suitable propensity score reweighting estimator. We find robust evidence for positive and sizable output effects and a pronounced reduction in the share of labor cost. With respect to employment, we document robust evidence for positive employment effects, especially for low- and high-skilled workers.
By focusing attention on heterogeneity in robot adoption within narrowly defined industries, our results provide novel evidence how robots affect industry heterogeneity. Importantly, we do not find any negative employment effects in those firms that start to adopt robots, even if we focus on specific skills or specific group of workers. Contrary, if anything we document that robot adopters start to hire more workers in the subsequent years, relative to the control group, i.e. their competitors that do not adopt robots. Put differently, negative employment effects might show up where they are ex-ante the least expected, namely in those firms that do not automate their production process. Hence, our study points to the importance of reallocation of resources withing industries, as robots are creating new opportunities for some firms, while simultaneously they contribute to a downfall for non-robot adopters.
Table 5: Employment effects of robot adoption

<table>
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<tr>
<th></th>
<th>Employment share</th>
<th>Labor costs share</th>
<th>Low-skilled</th>
<th>High-skilled</th>
<th>Manufacturing employment</th>
<th>Share of manufact. employment</th>
<th>Average wage</th>
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<td><strong>PANEL A - Selection Controls</strong></td>
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<td>Robot$_t$</td>
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<td>0.158</td>
<td>0.214</td>
<td>0.179</td>
<td>0.203</td>
<td>0.062</td>
<td>0.615</td>
</tr>
<tr>
<td>Industry-year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

| **PANEL B - Propensity Score** |                  |                   |             |              |                         |                              |              |
| Robot$_t$        | 0.0594***        | -0.0253**         | 0.0811***   | 0.000140     | 0.0512*                 | -0.00333                     | 0.0103       |
|                  | (0.0271)         | (0.0114)          | (0.0311)    | (0.0563)     | (0.0285)                | (0.00478)                    | (0.0166)     |
| Robot$_{t-4}$    | 0.0646*          | -0.0289**         | 0.0693*     | 0.0283       | 0.0633*                 | -0.00467                     | -0.0144      |
|                  | (0.0350)         | (0.0138)          | (0.0369)    | (0.0619)     | (0.0347)                | (0.00503)                    | (0.0183)     |
| Observations     | 4632             | 4595              | 4608        | 2592         | 4624                    | 4624                         | 4585         |
| R-squared        | 0.208            | 0.202             | 0.225       | 0.199        | 0.237                   | 0.121                        | 0.662        |
| Industry-year fixed effects | Yes             | Yes               | Yes         | Yes          | Yes                     | Yes                          | Yes          |

Notes: All dependent variables are expressed in logs except for the share of manufacturing employment. Robots is a 0/1 indicator variable equal to one if the firm uses robots in a period $t$. Selection controls in $t-4$ are firm’s deflated labor productivity (in logs), firm’s deflated capital intensity (in logs), firm’s deflated skill intensity (in logs), firm’s deflated R&D intensity (in logs), exporter, importer and foreign ownership status. 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. Clustered standard errors are given in parentheses. ***,*** denote significance at the 10%, 5%, 1% levels, respectively.
<table>
<thead>
<tr>
<th></th>
<th>PANEL A – Employment in $t$</th>
<th>PANEL B – Output in $t$</th>
<th>PANEL C – Exit in $t+1$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Robot-density$_t$</td>
<td>-0.193***</td>
<td>-0.222***</td>
<td>-0.210***</td>
</tr>
<tr>
<td></td>
<td>(0.0488)</td>
<td>(0.0716)</td>
<td>(0.0737)</td>
</tr>
<tr>
<td>Robot-density$_t$ × Robot-use</td>
<td>0.190***</td>
<td>0.313***</td>
<td>0.255***</td>
</tr>
<tr>
<td></td>
<td>(0.0732)</td>
<td>(0.0968)</td>
<td>(0.0988)</td>
</tr>
<tr>
<td>Observations</td>
<td>13372</td>
<td>6104</td>
<td>6104</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.080</td>
<td>0.125</td>
<td>0.128</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Selection controls</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry-year factor controls</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**Notes:** In columns (1) to (3) robot-density is defined as the share of sales by firms that use robots in total industry sales constructed from the ESEE data, whereas in columns (4) to (6) robot-density is defined as the (log of) stock of robots in an industry constructed from the IFR data. The variable robot-use is a 0/1 indicator variable equal to one if the firm uses robots (at least once) throughout the sample period. In Panel A (B) the dependent variable in all columns is the logarithm employment (real output). In Panel C the dependent variable in all columns is the logarithm employment (real output). In Panel C the dependent variable in all columns is the exit probability in $t+1$, i.e. an 0/1 indicator equal to one if the firm disappeared in the next period. Selection controls are firm’s deflated labor productivity in $t-4$ (in logs), firm’s deflated capital intensity in $t-4$ (in logs), firm’s deflated skill intensity in $t-4$ (in logs), firm’s deflated R&D intensity in $t-4$ (in logs), exporter status in $t-4$, importer status in $t-4$, foreign ownership status in $t-4$. Industry-year factor controls are computed as industry-means in capital, skill and R&D intensity. We add one to all factor intensity variables before taking logs in order to keep zero observations. Clustered standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.
References


A Appendix

A.1 Labor cost share for robot adopters vs. non-adopters

Figure A.1: Evolution of firm-level labor cost share (1990-2016)

Notes: The figure depicts the evolution of average firm labor cost share (defined as labor costs divided by the total production) in a balanced sample of firms from 1990-2016, separately for robot adopters (solid black line) and non-adopters (dashed grey line). 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.
### Table A.1: Robot adoption A.I: Probit cross-sectional and panel specification

**PANEL A: Cross-sectional specification**

<table>
<thead>
<tr>
<th></th>
<th>(1a)</th>
<th>(2a)</th>
<th>(3a)</th>
<th>(4a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base year labor productivity</td>
<td>0.197***</td>
<td>0.0863*</td>
<td>0.0931**</td>
<td>0.0356</td>
</tr>
<tr>
<td></td>
<td>(0.0425)</td>
<td>(0.0499)</td>
<td>(0.0448)</td>
<td>(0.0516)</td>
</tr>
<tr>
<td>Base year skill intensity</td>
<td>-2.373***</td>
<td></td>
<td></td>
<td>-2.838***</td>
</tr>
<tr>
<td></td>
<td>(0.718)</td>
<td></td>
<td></td>
<td>(0.793)</td>
</tr>
<tr>
<td>Base year exporter status</td>
<td></td>
<td></td>
<td></td>
<td>0.350***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0646)</td>
</tr>
<tr>
<td>Observations</td>
<td>3272</td>
<td>2732</td>
<td>3208</td>
<td>2689</td>
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<tr>
<td>Pseudo R-squared</td>
<td>0.061</td>
<td>0.100</td>
<td>0.089</td>
<td>0.114</td>
</tr>
</tbody>
</table>

**PANEL B: Panel specification**

<table>
<thead>
<tr>
<th></th>
<th>(1b)</th>
<th>(2b)</th>
<th>(3b)</th>
<th>(4b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged labor productivity</td>
<td>0.270***</td>
<td>0.116***</td>
<td>0.147***</td>
<td>0.0564</td>
</tr>
<tr>
<td></td>
<td>(0.0390)</td>
<td>(0.0404)</td>
<td>(0.0394)</td>
<td>(0.0403)</td>
</tr>
<tr>
<td>Lagged skill intensity</td>
<td>-0.890**</td>
<td></td>
<td>-1.213**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.442)</td>
<td></td>
<td>(0.485)</td>
<td></td>
</tr>
<tr>
<td>Lagged exporter status</td>
<td></td>
<td></td>
<td></td>
<td>0.231***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0537)</td>
</tr>
<tr>
<td>Observations</td>
<td>7225</td>
<td>6738</td>
<td>7157</td>
<td>6683</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.060</td>
<td>0.082</td>
<td>0.080</td>
<td>0.093</td>
</tr>
</tbody>
</table>

**Notes:** In Panel A 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, while in Panel B it is equal to one if the firm uses robots in a specific year and zero otherwise. 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). Exporter status is a dummy variable for positive exports. All estimates in Panel A (B) include industry-base-year (industry-year) fixed effects. Factor intensity controls are a firm’s capital intensity, defined as the firm’s deflated capital stock per worker, and R&D intensity as the firm’s deflated R&D expenditures relative to its deflated total sales (both in logs). Globalization controls are importer status, defined as a dummy variable for positive imports, and a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). We add one to all factor intensity variables before taking logs in order to keep zero observations. In Panel A all explanatory variables are measured in the base year defined as the first year the firm appears in the sample. In Panel B all explanatory variables are lagged by one year. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Moreover, in Panel B we condition on the firm not using robots in the previous year (or the most recent year for which robot data are available for that firm). Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.
Table A.2: Robot adoption A.II: Probit cross-sectional and panel specification

<table>
<thead>
<tr>
<th>PANEL A: Cross-sectional specification</th>
<th>(1a)</th>
<th>(2a)</th>
<th>(3a)</th>
<th>(4a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base year output</td>
<td>0.219***</td>
<td>0.184***</td>
<td>0.185***</td>
<td>0.153***</td>
</tr>
<tr>
<td></td>
<td>(0.0171)</td>
<td>(0.0220)</td>
<td>(0.0220)</td>
<td>(0.0267)</td>
</tr>
<tr>
<td>Base year skill intensity</td>
<td>-2.596***</td>
<td>-2.658***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.693)</td>
<td>(0.726)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base year exporter status</td>
<td>0.190***</td>
<td>0.180**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0661)</td>
<td>(0.0739)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3436</td>
<td>2839</td>
<td>3368</td>
<td>2793</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.105</td>
<td>0.123</td>
<td>0.111</td>
<td>0.127</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PANEL B: Panel specification</th>
<th>(1b)</th>
<th>(2b)</th>
<th>(3b)</th>
<th>(4b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged output</td>
<td>0.231***</td>
<td>0.211***</td>
<td>0.227***</td>
<td>0.201***</td>
</tr>
<tr>
<td></td>
<td>(0.0141)</td>
<td>(0.0171)</td>
<td>(0.0179)</td>
<td>(0.0203)</td>
</tr>
<tr>
<td>Lagged skill intensity</td>
<td>-1.498***</td>
<td>-1.454***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.486)</td>
<td>(0.491)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged exporter status</td>
<td>0.0356</td>
<td>0.0244</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0562)</td>
<td>(0.0595)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>7424</td>
<td>6891</td>
<td>7350</td>
<td>6831</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.112</td>
<td>0.115</td>
<td>0.113</td>
<td>0.115</td>
</tr>
</tbody>
</table>

Industry(-base)-year fixed effects    | Yes | Yes | Yes | Yes |
Factor intensity controls      | No  | Yes | No  | Yes |
Globalization controls        | No  | No  | Yes | Yes |

Notes: In Panel A 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, while in Panel B it is equal to one if the firm uses robots in a specific year and zero otherwise. Output is the firm’s deflated output value (in logs). Skill intensity is the firm’s share of workers with a five-year university degree (in logs). Exporter status is a dummy variable for positive exports. All estimates in Panel A (B) include industry-base-year (industry-year) fixed effects. Factor intensity controls are a firm’s capital intensity, defined as the firm’s deflated capital stock per worker, and R&D intensity as the firm’s deflated R&D expenditures relative to its deflated total sales (both in logs). Globalization controls are importer status, defined as a dummy variable for positive imports, and a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). We add one to all factor intensity variables before taking logs in order to keep zero observations. In Panel A all explanatory variables are measured in the base year defined as the first year the firm appears in the sample. In Panel B all explanatory variables are lagged by one year. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Moreover, in Panel B we condition on the firm not using robots in the previous year (or the most recent year for which robot data are available for that firm). Robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.
<table>
<thead>
<tr>
<th>Productivity</th>
<th>Robot adoption (0/1 indicator)</th>
<th>Labor productivity</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td>(5) (6) (7) (8)</td>
<td></td>
</tr>
<tr>
<td><strong>Base year 2nd quartile</strong></td>
<td><strong>0.0443</strong>*</td>
<td>0.0185</td>
<td>0.0378***</td>
</tr>
<tr>
<td></td>
<td>(0.0167)</td>
<td>(0.0184)</td>
<td>(0.0139)</td>
</tr>
<tr>
<td><strong>Base year 3rd quartile</strong></td>
<td><strong>0.0531</strong>*</td>
<td>0.0213</td>
<td>0.0792***</td>
</tr>
<tr>
<td></td>
<td>(0.0166)</td>
<td>(0.0189)</td>
<td>(0.0148)</td>
</tr>
<tr>
<td><strong>Base year 4th quartile</strong></td>
<td><strong>0.0780</strong>*</td>
<td>0.0179</td>
<td>0.205***</td>
</tr>
<tr>
<td></td>
<td>(0.0170)</td>
<td>(0.0207)</td>
<td>(0.0173)</td>
</tr>
<tr>
<td><strong>Base year skill intensity</strong></td>
<td>-0.400***</td>
<td>-0.407***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.101)</td>
<td></td>
</tr>
<tr>
<td><strong>Base year exporter status</strong></td>
<td>0.0573***</td>
<td>0.0346**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0161)</td>
<td>(0.0160)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4053</td>
<td>3443</td>
<td>4221</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.111</td>
<td>0.161</td>
<td>0.141</td>
</tr>
<tr>
<td>Industry-base-year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Factor intensity controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Globalization controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

**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 productivity distribution of the industry in which it is active. Columns (1) and (2) do this based on labor productivity, i.e., the firm’s deflated value added per worker, while columns (3) and (4) use output, i.e., the firm’s deflated output value. Skill intensity is the firm’s share of workers with a five-year university degree (in logs). Exporter status is a dummy variable for positive exports. Factor intensity controls are a firm’s capital intensity, defined as the firm’s deflated capital stock per worker, and R&D intensity as the firm’s deflated R&D expenditures relative to its deflated total sales (both in logs). Globalization controls are importer status, defined as a dummy variable for positive imports, and a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). We add one to all factor intensity variables before taking logs in order to keep zero observations. 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.4: Robot adoption based on productivity quartiles: linear panel specification

<table>
<thead>
<tr>
<th></th>
<th>Robot adoption (0/1 indicator)</th>
<th>Labor productivity</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td><strong>Productivity</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged 2nd quartile</td>
<td>0.0166**</td>
<td>0.00126</td>
<td>0.0242***</td>
</tr>
<tr>
<td></td>
<td>(0.00827)</td>
<td>(0.00855)</td>
<td>(0.00725)</td>
</tr>
<tr>
<td>Lagged 3rd quartile</td>
<td>0.0464***</td>
<td>0.0121</td>
<td>0.0615***</td>
</tr>
<tr>
<td></td>
<td>(0.00915)</td>
<td>(0.00972)</td>
<td>(0.00862)</td>
</tr>
<tr>
<td>Lagged 4th quartile</td>
<td>0.0719***</td>
<td>0.0169</td>
<td>0.149***</td>
</tr>
<tr>
<td></td>
<td>(0.00983)</td>
<td>(0.0110)</td>
<td>(0.0102)</td>
</tr>
<tr>
<td>Lagged skill intensity</td>
<td>-0.151**</td>
<td></td>
<td></td>
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<td></td>
<td>(0.0633)</td>
<td></td>
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<tr>
<td>Lagged exporter status</td>
<td>0.0250***</td>
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</tr>
<tr>
<td></td>
<td>(0.00820)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>7368</td>
<td>6879</td>
<td>7535</td>
</tr>
<tr>
<td><strong>R-squared</strong></td>
<td>0.041</td>
<td>0.059</td>
<td>0.068</td>
</tr>
<tr>
<td>Industry-year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Factor intensity controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Globalization controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

**Notes:** The dependent variable in all columns is a 0/1 indicator variable equal to one if the firm uses robots and zero otherwise. The regressions include a full set of dummy variables indicating the firm’s (quartile) position in the productivity distribution of the industry in which it is active. Capital intensity is the firm’s deflated capital stock per worker. Skill intensity is the firm’s share of workers with a five-year university degree (in logs). Exporter status is a dummy variable for positive exports. Factor intensity controls are a firm’s capital intensity, defined as the firm’s deflated capital stock per worker, and R&D intensity as the firm’s deflated R&D expenditures relative to its deflated total sales (both in logs). Globalization controls are importer status, defined as a dummy variable for positive imports, and a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). We add one to all factor intensity variables before taking logs in order to keep zero observations. All explanatory variables are lagged by one year. The sample is restricted to firms that do not use robots in the first year they appear in the sample. Moreover, we condition on the firm not using robots in the previous year (or the most recent year for which robot data are available for that firm). Robust standard errors (clustered by firm) are given in parentheses. *, **, *** denote significance at the 10%, 5%, 1% levels, respectively.
A.3 Propensity score estimates

In column (1) of Table A.5 we present univariate 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 multivariate 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.5: Propensity scores estimation equation (probit specification)

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

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

A.4 Details to data from the International Federation of Robotics (IFR)
Table A.6: Sector mapping IFR to ESEE

<table>
<thead>
<tr>
<th>Description</th>
<th>SEPI website</th>
<th>Corresponding IFR industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Meat products</td>
<td>10-12</td>
<td>Food and beverages</td>
</tr>
<tr>
<td>2. Food and tobacco</td>
<td>10-12</td>
<td>Food and beverages</td>
</tr>
<tr>
<td>3. Beverage</td>
<td>10-12</td>
<td>Food and beverages</td>
</tr>
<tr>
<td>4. Textiles and clothing</td>
<td>13-15</td>
<td>Textiles</td>
</tr>
<tr>
<td>5. Leather, fur and footwear</td>
<td>13-15</td>
<td>Textiles</td>
</tr>
<tr>
<td>6. Timber</td>
<td>16</td>
<td>Wood and furniture</td>
</tr>
<tr>
<td>7. Paper</td>
<td>17-18</td>
<td>Paper</td>
</tr>
<tr>
<td>8. Printing</td>
<td>17-18</td>
<td>Paper</td>
</tr>
<tr>
<td>9. Chemicals and pharmaceuticals</td>
<td>19 &amp; 20-21</td>
<td>Pharmaceuticals, cosmetics &amp; other chemical products n.e.c. &amp; 229</td>
</tr>
<tr>
<td>10. Plastic and rubber products</td>
<td>22</td>
<td>Rubber and plastic products (non-automotive)</td>
</tr>
<tr>
<td>11. Nonmetal mineral products</td>
<td>23</td>
<td>Glass, ceramics, stone, mineral products</td>
</tr>
<tr>
<td>12. Basic metal products</td>
<td>24</td>
<td>Basic metals &amp; 289</td>
</tr>
<tr>
<td>13. Fabricated metal products</td>
<td>25</td>
<td>Metal products</td>
</tr>
<tr>
<td>14. Machinery and equipment</td>
<td>28</td>
<td>Industrial machinery</td>
</tr>
<tr>
<td>15. Computer products, electronics and optical</td>
<td>275</td>
<td>Household/domestic appliances &amp; 262</td>
</tr>
<tr>
<td>16. Electric materials and accessories</td>
<td>271</td>
<td>Electrical machinery n.e.c. &amp; 260</td>
</tr>
<tr>
<td>17. Vehicles and accessories</td>
<td>29</td>
<td>Automotive</td>
</tr>
<tr>
<td>18. Other transport equipment</td>
<td>30</td>
<td>Other vehicles</td>
</tr>
<tr>
<td>19. Furniture</td>
<td>16</td>
<td>Wood and furniture</td>
</tr>
<tr>
<td>20. Other manufacturing</td>
<td>91</td>
<td>All other manufacturing branches</td>
</tr>
</tbody>
</table>

Notes: This table provides information on how we map 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).
S. Online Supplement (not intended for publication)

S.1 Theoretical details to Section 3

In this supplement we provide derivation details to the results presented in Section 3 in the main text of the paper. In our theoretical perspective on firm-level robot adoption firms differ in their baseline productivity $\phi(\omega)$ and the type of tasks $N(\omega)$. In a first step, let us focus on only one-dimensional heterogeneity by assuming that all firms have to perform the same task-range, determined by $N(\omega) = N$. Hence, firms are fully described by their productivity $\phi$ and we can skip firm index $\omega$ to save on notation. We can write firm profits for robot adopters and non-adopters accordingly as

$$\pi(\phi) = (1 - \beta)A \left\{ \frac{1}{\beta} \left[ \gamma(N, N - 1)w^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \right\}^{-\frac{\beta}{1-\sigma}} - F,$$  \hspace{1cm} (S.1)

$$\pi^a(\phi) = (1 - \beta)A \left\{ \frac{1}{\beta} \left[ \eta(N,I)r^{1-\sigma} + \gamma(N,I)w^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \right\}^{-\frac{\beta}{1-\sigma}} - F - F^a.$$  \hspace{1cm} (S.2)

Due to our assumptions on the comparative advantage of robots in all tasks $i \leq I$ we know that $[\gamma(N, N - 1)w^{1-\sigma}] < [\eta(N,I)r^{1-\sigma} + \gamma(N,I)w^{1-\sigma}]$ holds. Let us normalize the left hand site and set $[\gamma(N, N - 1)w^{1-\sigma}]^{\frac{1}{1-\sigma}} = 1$ and define $[\eta(N,I)r^{1-\sigma} + \gamma(N,I)w^{1-\sigma}]^{\frac{1}{1-\sigma}} = 1/\eta$ with $\eta > 1$, w.l.o.g. Furthermore, let us choose $F^a = (\alpha - 1)F$ with $\alpha > 1$. We can thus rewrite profits as

$$\pi(\phi) = (1 - \beta)A \left\{ \frac{1}{\beta} \phi \right\}^{-\frac{\beta}{1-\sigma}} - F;$$  \hspace{1cm} (S.3)

$$\pi^a(\phi) = (1 - \beta)A \left\{ \frac{1}{\beta} \phi \eta \right\}^{-\frac{\beta}{1-\sigma}} - \alpha F.$$  \hspace{1cm} (S.4)

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

$$\phi^r = \phi^* \left( \frac{\alpha - 1}{\eta^{\frac{\beta}{1-\sigma}} - 1} \right)^{\frac{1-\beta}{\beta}}.$$  \hspace{1cm} (S.5)

Finally, let us define the share of firms $s_r$ that use robots as

$$s_r \equiv \frac{1 - G(\phi^r)}{1 - G(\phi^*)},$$  \hspace{1cm} (S.6)

where $G(\cdot)$ denotes the cumulative distribution function. From inspection of Equation (S.5) we can conclude that lower fixed costs for robot adoption or a higher efficiency of robots raises the share of robot adopters, i.e. $\partial s_r/\partial \alpha < 0$ and $\partial s_r/\partial \eta > 0$.

Discussing the implications on 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 hetero-
geneous firms, we refer the interested reader for details to Melitz (2003). Here, we briefly outline how the endogenous cut-off productivity $\phi^*$ can be determined. Specifically, it is determined by two conditions. The first condition uses the relation between the average profit per firm and the cutoff productivity level, the so-called zero-cutoff productivity. It can be computed as the average profits over all active firms, that is

$$\bar{\pi} = (1 - \beta)A \left( \frac{1}{\beta \tilde{\phi}} \right)^{-\frac{\beta}{1-\beta}} - F - F(\alpha - 1) \frac{1 - G(\phi^*)}{1 - G(\phi^*)}, \quad (S.7)$$

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

$$\tilde{\phi} \equiv \left( \int_{\phi^*}^{\phi^r} \phi^{1-\beta} \frac{g(\phi)}{1 - G(\phi^*)} d\phi + \int_{\phi^r}^{\infty} (\eta\phi)^{1-\beta} \frac{g(\phi)}{1 - G(\phi^*)} d\phi \right)^{\frac{1-\beta}{\beta}}. \quad (S.8)$$

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 (discounted by $\delta$) profits. Formally, this reads:

$$\bar{\pi} = \frac{\delta f_e}{1 - G(\phi^*)}. \quad (S.9)$$

Both equations can be used to determine a unique cut-off productivity level. Especially, this allows us to conclude that lower fixed costs for robot adoption or a higher efficiency of robots 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, which raises the cut-off productivity at which firms are able to survive in the market. Put differently, increasing robot exposure raises the exit rates of non-robot firms and reduces their output and employment. This completes the discussion to the first paragraph of Section 3.1.

When allowing for trade with a symmetric partner country, we can split the type of firms into four groups, namely combinations among non-robot adopters vs. robot adopters (indicated by upper script $a$) and exporters vs. non-exporters (indicated by lower script $x$ and $d$, respectively). Specifically, we can write firm profits for these four different types as

$$\pi_d(\phi) = (1 - \beta)A \left\{ \frac{1}{\beta} \left[ \gamma(N, N - 1) w^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \right\}^{-\frac{\beta}{1-\beta}} - F, \quad (S.10)$$

$$\pi_a(\phi) = (1 - \beta)A \left\{ \frac{1}{\beta} \left[ \eta(N, I) r^{1-\sigma} + \gamma(N, I) w^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \right\}^{-\frac{\beta}{1-\beta}} - F - F^a, \quad (S.11)$$

$$\pi_x(\phi) = \left( 1 + \tau^{-\frac{\beta}{1-\beta}} \right) (1 - \beta)A \left\{ \frac{1}{\beta} \left[ \gamma(N, N - 1) w^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \right\}^{-\frac{\beta}{1-\beta}} - F - F^x, \quad (S.12)$$
\[ \pi_d(\phi) = \left(1 + \tau^{-\frac{1}{1-\beta}}\right)(1 - \beta)A\left\{ \frac{1}{\beta} \left[ \eta(N, I)r^{1-\sigma} + \gamma(N, I)w^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \right\}^{-\frac{\beta}{1-\sigma}} - F - F^a - F^x. \]  
(S.13)

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

\[ \pi_d(\phi) = (1 - \beta)A\left( \frac{1}{\beta \phi} \right)^{-\frac{\beta}{1-\beta}} - F, \]  
(S.14)

\[ \pi_d^a(\phi) = (1 - \beta)A\left( \frac{1}{\beta \phi \eta} \right)^{-\frac{\beta}{1-\beta}} - \alpha F, \]  
(S.15)

\[ \pi_x(\phi) = \left(1 + \tau^{-\frac{\beta}{1-\beta}}\right)(1 - \beta)A\left( \frac{1}{\beta \phi} \right)^{-\frac{\beta}{1-\beta}} - F - F^x, \]  
(S.16)

\[ \pi_x^r(\phi) = \left(1 + \tau^{-\frac{\beta}{1-\beta}}\right)(1 - \beta)A\left( \frac{1}{\beta \phi \eta} \right)^{-\frac{\beta}{1-\beta}} - \alpha F - F^x. \]  
(S.17)

This system is (almost, except of different variable labels) identical to the problem described in (Bustos, 2011, p.310). We can thus build on her insights and follow the same steps. Accordingly, we focus on cost and parameter conditions, such that the least productive firms only serve 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. Notably, the descriptive analysis in the main text revealed that the share of robot firms is clearly below the share of exporting firms. It is therefore plausible to assume that the marginal exporter is a non-robot adopter. As shown in Bustos (2011), this is the case with sufficiently high fixed costs of robot adoption relative to exporting. The exporter cut-off \( \phi^x \) is determined by the indifference condition \( \pi_d(\phi^x) = \pi_x(\phi^x) \). Combining it with \( \pi_d(\phi^* ) = 0 \) entails

\[ \phi^x = \phi^* \tau \left( \frac{F^x}{F} \right)^{\frac{1-\beta}{\beta}}. \]  
(S.18)

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

\[ \phi^r = \phi^* \frac{1}{\left(1 + \tau^{-\frac{\beta}{1-\beta}}\right)^{\frac{\beta}{1-\beta}}} \left( \frac{\alpha - 1}{\eta^{\frac{\beta}{1-\beta}} - 1} \right)^{\frac{1-\beta}{\beta}}. \]  
(S.19)

Using Equation (S.19) we can conclude that a reduction in variable trade costs \( \tau \) raises the share of firms that adopt robots, i.e. \( \partial s_r/\partial \tau < 0 \). As discussed in detail in Bustos (2011), we know that the incentives for robot-adoption are higher for exporting firms, as the gains from investments – the
reduction in variable production costs – can be scaled up to a larger customer base in home and foreign. This completes the discussion to the second paragraph of Section 3.1.

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

\[
x(\omega, i) = 1 \left[ i \leq I \right] \eta(i)k(\omega, i) + \gamma_l(i)l_l(\omega, i) + \gamma_h(i)l_h(\omega, i).
\]

(S.20)

In such an environment firms will not only compare the production costs of robots and human capital across tasks but also compare the effective labor costs in each task among the two skill types, that is \( w_l/\gamma_l(i) \) to \( w_h/\gamma_h(i) \). The task level production function in (S.20) 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 co-workers 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 indifferent between hiring low-skilled or high-skilled workers, at prevailing skill intensity \( s \equiv w_h/w_l \). Put differently, in \( z \) the unit costs of task performance are the same irrespective of the assigned skill type \( k = l, h \), which establishes

\[
w_l/\gamma_l(z) = w_h/\gamma_h(z).
\]

(S.21)

Koch (2016) discusses parameter constraints (on the comparative advantage schedule, factor endowments, etc.) within a general equilibrium framework that guarantees the existence of an interior solution, \( z \in (N - 1, N) \). Intuitively, it requires a skill premium that exceeds the productivity advantage of high-skilled workers in some tasks. Under this constraint, we can come up with the conclusion 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 that robots can not automate all tasks performed by low-skilled workers, that is \( I < z \), we get for the unit production costs

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

(S.22)

where \( \eta(N, I) \equiv \left( \int_{N-I}^I \eta(i)^{\sigma-1} di \right)^{\frac{1}{\sigma}} \), \( \gamma_l(I, z) \equiv \left( \int_z^I \gamma_l(i)^{\sigma-1} di \right)^{\frac{1}{\sigma}} \) 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 used this extension with two skill types to draw the conclusion, that firms with a higher skill intensity are less likely to adopt robots. Therefore, we now also consider heterogeneity of firms in the type of tasks, determined by \( N \). For the ease of exposition assume that task range for some firms is given by \( N \) while firms with a higher task complexity have to perform tasks within the range \((N_c^c - 1, N_c^c)\).\(^{33}\) Furthermore, suppose that \( I > N_c - 1 \), so even in the case of a higher

\(^{33}\)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 that provide extensions in this direction 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 in Harrigan and Reshef (2015) firms produce by employing low- and high-skilled workers and firms differ in their baseline productivity \( \phi \) and the Cobb-Douglas share parameter
task-complexity, (some) tasks are automatable. Figure S.1 is illustrating the situation for two firms with low and high task complexity. It is evident that firms that have to perform tasks with a higher task complexity 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. Put differently, firms with a lower skill intensity (reflecting a lower task-complexity and thus higher share of automatable tasks) are more likely to adopt robots. This completes the discussion to the third paragraph of Section 3.1.

Figure S.1: Skill allocation and automatable tasks for different task complexities

S.2 Robustness analysis on the treatment effect of robot adoption

As stated in Section 2 information on robot usage at the firm level comes from the 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”. Here, we show that robot adoption is different to using alternative systems that are proposed in the survey question. Therefore, we create three additional indicators, called CAM, CAD or FLEX. They are construct as 0/1 indicator variables equal to one if the firm uses computer-digital machine tools (CAM), computer-assisted design (CAD), or, combination of some of the above systems through a central computer, e.g. CAM, flexible manufacturing systems, etc. (FLEX). Table S.1 provides summary statistics on these indicators together with our robot dummy variable from the main text. Table S.2 list correlations among the four indicators. From the tables we can inspect that robots are uses less frequently in the production process com-

α that determines the skill-intensity. They proceed by describing firms by their “competitiveness”, determined by both ϕ and α and apply the theory of copulas from mathematical statistics to determine the distribution of firms competitiveness and allowing for flexible correlations among ϕ and α. Another example in that context is Capuano et al. (2017), who allow for two-dimensional heterogeneity in the context of offshoring. In their framework firms differ in the range of tasks and the share of offshorable tasks. Since we restrict our analysis mainly to derive selection and treatment effects of robot adoption at the firm level, it does not require to solve the model in general equilibrium. Going in this direction requires many additional assumptions on the endowments, model parameters, etc. which is way beyond the focus of our paper.
pared to the three alternative systems, while there is a slightly positive correlations among all of them.

In Section 5.3 we briefly summarize results on the potential treatment effects of using these alternative systems in the production process. Thereby, we exactly follow our strategy from the treatment analysis in Section 5. In a first step, we investigate the output effects of these systems. We estimate Eq. (8) and replace the robots indicator with our indicators for CAM, CAD or FLEX. In Table S.3, S.4 and S.5 we report our estimates, thereby restricting the sample to firms that do not use CAM, CAD or FLEX in the first year they appear in the sample, respectively. It turns out that the adoption of computer-digital machine tools or flexible manufacturing systems through a central computer raises firm output. However, in contrast to robot adoption, the estimates turn out to be less important and they also loose significance. Adopting computer-assisted designs even turns out to have no statistically significant effect on output. In a final robustness analysis on the output effects of robot adoption we also introduce the alternative systems as further control variables. Table S.6 reports the estimates. It turns out that including the additional controls has no impact on the significance and the size on our estimated coefficients for robot adoption.

We then proceed by investigating the employment affects of these alternative systems, again, following our strategy from the main text. Table S.7 report the employment effects from adoption CAM, CAD or FLEX. Similar to robots, we find positive employment effects for the three systems, both in terms of significance and size. However, there is one important difference to robot adoption. None of these systems reduce the labor cost share, as can be inferred from columns (2a), (2b) and (2c) in Table S.7. Lastly, we introduce the alternative systems as further control variables in the analysis of robots on employment. Table S.8 and Table S.9 reports the estimates with selection controls for robot adoption or using propensity score estimates, respectively. It turns out that including the additional controls has no impact on the significance and the size on our estimated coefficients for robot adoption on different employment outcomes.

Table S.1: Descriptive statistics on systems in the production process

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>STD.</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Robot</td>
<td>0.086</td>
<td>0.281</td>
<td>12808</td>
</tr>
<tr>
<td>CAM</td>
<td>0.358</td>
<td>0.479</td>
<td>12808</td>
</tr>
<tr>
<td>CAD</td>
<td>0.266</td>
<td>0.442</td>
<td>12808</td>
</tr>
<tr>
<td>FLEX</td>
<td>0.244</td>
<td>0.430</td>
<td>12808</td>
</tr>
</tbody>
</table>

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 S.2: Correlations among different systems in the production process

<table>
<thead>
<tr>
<th></th>
<th>Robot</th>
<th>CAM</th>
<th>CAD</th>
<th>FLEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Robot</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAM</td>
<td>0.199*</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAD</td>
<td>0.195*</td>
<td>0.330*</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>FLEX</td>
<td>0.114*</td>
<td>0.200*</td>
<td>0.126*</td>
<td>1.000</td>
</tr>
</tbody>
</table>

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.

Table S.3: Output effects of computer-digital machine tools

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CAM_t$</td>
<td>0.0661**</td>
<td>0.105***</td>
<td>0.0657**</td>
<td>0.106***</td>
</tr>
<tr>
<td></td>
<td>(0.0278)</td>
<td>(0.0343)</td>
<td>(0.0289)</td>
<td>(0.0350)</td>
</tr>
<tr>
<td>$CAM_{t-4}$</td>
<td>0.0794***</td>
<td>0.0865**</td>
<td>0.0870***</td>
<td>0.0766**</td>
</tr>
<tr>
<td></td>
<td>(0.0287)</td>
<td>(0.0337)</td>
<td>(0.0295)</td>
<td>(0.0346)</td>
</tr>
<tr>
<td>$CAM_{t+4}$</td>
<td>0.0584</td>
<td>0.0350</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0382)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 a logarithm of real output. Selection controls (in $t-4$) are firm’s deflated labor productivity (in logs), firm’s deflated capital intensity (in logs), firm’s deflated skill intensity (in logs), firm’s deflated R&D intensity (in logs), exporter, importer and foreign ownership status. 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. Clustered standard errors are given in parentheses. ***,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table S.4: Output effects of computer-assisted design

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CAD_t$</td>
<td>0.0223</td>
<td>0.0269</td>
<td>0.0276</td>
<td>0.0318</td>
</tr>
<tr>
<td></td>
<td>(0.0340)</td>
<td>(0.0397)</td>
<td>(0.0370)</td>
<td>(0.0436)</td>
</tr>
<tr>
<td>$CAD_{t-4}$</td>
<td>0.0535</td>
<td>0.0702</td>
<td>0.0503</td>
<td>0.0584</td>
</tr>
<tr>
<td></td>
<td>(0.0356)</td>
<td>(0.0448)</td>
<td>(0.0371)</td>
<td>(0.0463)</td>
</tr>
<tr>
<td>$CAD_{t+4}$</td>
<td>-0.0255</td>
<td>-0.0241</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0398)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations | 4493 | 2532 | 4115 | 2326 |
R-squared | 0.219 | 0.284 | 0.232 | 0.285 |
Selection controls | No | No | 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 a logarithm of real output. Selection controls (in $t-4$) are firm’s deflated labor productivity (in logs), firm’s deflated capital intensity (in logs), firm’s deflated skill intensity (in logs), firm’s deflated R&D intensity (in logs), exporter, importer and foreign ownership status. 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. Clustered standard errors are given in parentheses. ***,*** denote significance at the 10%, 5%, 1% levels, respectively.

*34We do not report estimates using propensity score estimates, since they are obtained for robot adoption, based on the theoretical predictions and empirical results on the selection analysis throughout Sections 3 and 4.*
## Table S.5: Output effects of flexible manufacturing systems

<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td>$FLEX_t$</td>
<td>0.0845***</td>
<td>0.0712*</td>
<td>0.0797**</td>
<td>0.0654*</td>
</tr>
<tr>
<td></td>
<td>(0.0308)</td>
<td>(0.0368)</td>
<td>(0.0315)</td>
<td>(0.0394)</td>
</tr>
<tr>
<td>$FLEX_{t-4}$</td>
<td>0.0969**</td>
<td>0.100*</td>
<td>0.0926**</td>
<td>0.0996*</td>
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<tr>
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<td>(0.0395)</td>
<td>(0.0553)</td>
<td>(0.0426)</td>
<td>(0.0593)</td>
</tr>
<tr>
<td>$FLEX_{t+4}$</td>
<td></td>
<td>-0.0134</td>
<td></td>
<td>-0.00645</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0358)</td>
<td></td>
<td>(0.0378)</td>
</tr>
<tr>
<td>Observations</td>
<td>3366</td>
<td>1743</td>
<td>3131</td>
<td>1620</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.287</td>
<td>0.321</td>
<td>0.309</td>
<td>0.340</td>
</tr>
<tr>
<td>Selection controls</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry-year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**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 a logarithm of real output. Selection controls (in $t-4$) are firm’s deflated labor productivity (in logs), firm’s deflated capital intensity (in logs), firm’s deflated skill intensity (in logs), firm’s deflated R&D intensity (in logs), exporter, importer and foreign ownership status. 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. Clustered standard errors are given in parentheses. *, **, *** denote significance at the 10%, 5%, 1% levels, respectively.
Table S.6: Output effects of robot adoption controlling for other systems in the production process

<table>
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<tr>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Robots</strong>&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.157***</td>
<td>0.106***</td>
<td>0.162***</td>
<td>0.120***</td>
<td>0.126***</td>
<td>0.119**</td>
</tr>
<tr>
<td></td>
<td>(0.0289)</td>
<td>(0.0344)</td>
<td>(0.0315)</td>
<td>(0.0370)</td>
<td>(0.0385)</td>
<td>(0.0495)</td>
</tr>
<tr>
<td><strong>Robots</strong>&lt;sub&gt;t−4&lt;/sub&gt;</td>
<td>0.121***</td>
<td>0.126***</td>
<td>0.119***</td>
<td>0.111**</td>
<td>0.121***</td>
<td>0.0815</td>
</tr>
<tr>
<td></td>
<td>(0.0325)</td>
<td>(0.0446)</td>
<td>(0.0337)</td>
<td>(0.0468)</td>
<td>(0.0415)</td>
<td>(0.0545)</td>
</tr>
<tr>
<td><strong>Robots</strong>&lt;sub&gt;t+4&lt;/sub&gt;</td>
<td>0.0743**</td>
<td>0.0471</td>
<td></td>
<td>0.0724</td>
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<tr>
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<td>(0.0383)</td>
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<td>(0.0478)</td>
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<td></td>
</tr>
<tr>
<td><strong>CAM</strong>&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.0436*</td>
<td>0.0340</td>
<td>0.0422*</td>
<td>0.0247</td>
<td>0.0671**</td>
<td>0.0476</td>
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<td>(0.0299)</td>
<td>(0.0236)</td>
<td>(0.0304)</td>
<td>(0.0275)</td>
<td>(0.0351)</td>
</tr>
<tr>
<td><strong>CAM</strong>&lt;sub&gt;t−4&lt;/sub&gt;</td>
<td>0.0297</td>
<td>-0.00699</td>
<td>0.0255</td>
<td>-0.0190</td>
<td>0.0332</td>
<td>-0.0203</td>
</tr>
<tr>
<td></td>
<td>(0.0227)</td>
<td>(0.0272)</td>
<td>(0.0233)</td>
<td>(0.0279)</td>
<td>(0.0252)</td>
<td>(0.0308)</td>
</tr>
<tr>
<td><strong>CAM</strong>&lt;sub&gt;t+4&lt;/sub&gt;</td>
<td>0.00971</td>
<td>-0.00130</td>
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<td>0.0502</td>
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<td>(0.0295)</td>
<td></td>
<td>(0.0323)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>CAD</strong>&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.0189</td>
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<td>-0.0296</td>
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<tr>
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<td>(0.0324)</td>
<td>(0.0410)</td>
<td>(0.0396)</td>
<td>(0.0464)</td>
</tr>
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<td><strong>CAD</strong>&lt;sub&gt;t−4&lt;/sub&gt;</td>
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<td>0.00372</td>
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<td>0.0209</td>
</tr>
<tr>
<td></td>
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<td>(0.0351)</td>
<td>(0.0291)</td>
<td>(0.0362)</td>
<td>(0.0311)</td>
<td>(0.0415)</td>
</tr>
<tr>
<td><strong>CAD</strong>&lt;sub&gt;t+4&lt;/sub&gt;</td>
<td>-0.0216</td>
<td>-0.00727</td>
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<td>-0.0168</td>
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<tr>
<td></td>
<td>(0.0355)</td>
<td>(0.0380)</td>
<td></td>
<td>(0.0439)</td>
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<td></td>
</tr>
<tr>
<td><strong>FLEX</strong>&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.0256</td>
<td>0.0334</td>
<td>0.0250</td>
<td>0.0401</td>
<td>0.0207</td>
<td>0.0256</td>
</tr>
<tr>
<td></td>
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<td>(0.0283)</td>
<td>(0.0266)</td>
<td>(0.0285)</td>
<td>(0.0281)</td>
<td>(0.0350)</td>
</tr>
<tr>
<td><strong>FLEX</strong>&lt;sub&gt;t−4&lt;/sub&gt;</td>
<td>-0.00607</td>
<td>-0.00357</td>
<td>-0.00972</td>
<td>-0.0122</td>
<td>-0.0232</td>
<td>-0.00480</td>
</tr>
<tr>
<td></td>
<td>(0.0217)</td>
<td>(0.0257)</td>
<td>(0.0238)</td>
<td>(0.0290)</td>
<td>(0.0260)</td>
<td>(0.0318)</td>
</tr>
<tr>
<td><strong>FLEX</strong>&lt;sub&gt;t+4&lt;/sub&gt;</td>
<td>-0.0240</td>
<td>-0.0248</td>
<td></td>
<td>-0.00570</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.0286)</td>
<td>(0.0283)</td>
<td></td>
<td>(0.0361)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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  
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 a logarithm of real output. Selection controls (in t − 4) are firm’s deflated labor productivity (in logs), firm’s deflated capital intensity (in logs), firm’s deflated skill intensity (in logs), firm’s deflated R&D intensity (in logs), exporter, importer and foreign ownership status. 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. Clustered standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.
Table S.7: Employment effects of different systems in the production process

<table>
<thead>
<tr>
<th>Computer-digital machine tools</th>
<th>Employment share</th>
<th>Labor costs</th>
<th>Low-skilled</th>
<th>High-skilled</th>
<th>Manufacturing employment</th>
<th>Share of manuf. employment</th>
<th>Average wage</th>
</tr>
</thead>
<tbody>
<tr>
<td>( CAM_t )</td>
<td>0.0690***</td>
<td>0.00637</td>
<td>0.0587**</td>
<td>0.0866</td>
<td>0.0545**</td>
<td>-0.00760**</td>
<td>0.00954</td>
</tr>
<tr>
<td>( CAM_{t-4} )</td>
<td>0.0557**</td>
<td>-0.00499</td>
<td>0.0500*</td>
<td>0.0549</td>
<td>0.0349</td>
<td>-0.0117**</td>
<td>0.0167</td>
</tr>
<tr>
<td>Observations</td>
<td>3187</td>
<td>3168</td>
<td>3164</td>
<td>1760</td>
<td>3181</td>
<td>3181</td>
<td>3160</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.274</td>
<td>0.201</td>
<td>0.278</td>
<td>0.206</td>
<td>0.253</td>
<td>0.076</td>
<td>0.656</td>
</tr>
</tbody>
</table>

| Computer-assisted design      | (1b)             | (2b)       | (3b)       | (4b)        | (5b)        | (6b)               | (7b)  |
| \( CAD_t \)                  | 0.0209           | 0.00386    | 0.0236     | 0.0280      | 0.0358      | 0.00570             | 0.0232*    |
| \( CAD_{t-4} \)              | 0.0725***        | -0.0000145 | 0.0640**   | 0.181***    | 0.0686**    | -0.00548            | -0.00371   |
| Observations                  | 4116             | 4092       | 4088       | 2290        | 4108        | 4108                | 4084       |
| R-squared                     | 0.214            | 0.150      | 0.222      | 0.203       | 0.212       | 0.047               | 0.631      |

| Flexible manufacturing systems| (1c)             | (2c)       | (3c)       | (4c)        | (5c)        | (6c)               | (7c)  |
| \( FLEX_t \)                 | 0.0796***        | 0.00309    | 0.0774***  | 0.127***    | 0.0811***   | 0.00146             | -0.0106    |
| \( FLEX_{t-4} \)             | 0.0955***        | -0.00175   | 0.105***   | 0.130**     | 0.107***    | 0.00131             | -0.0127    |
| Observations                  | 3132             | 3111       | 3111       | 1737        | 3130        | 3130                | 3105       |
| R-squared                     | 0.274            | 0.212      | 0.286      | 0.232       | 0.261       | 0.088               | 0.645      |

| Industry-year fixed effects   | Yes              | Yes        | Yes        | Yes         | Yes         | Yes                 | Yes   |
| Selection controls            | Yes              | Yes        | Yes        | Yes         | Yes         | Yes                 | Yes   |

Notes: All dependent variables are expressed in logs except for the share of manufacturing employment. \( CAM \) 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 \( t \). Selection controls in \( t-4 \) are firm’s deflated labor productivity (in logs), firm’s deflated capital intensity (in logs), firm’s deflated skill intensity (in logs), firm’s deflated R&D intensity (in logs), exporter, importer and foreign ownership status. 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. Clustered standard errors are given in parentheses. ***, *** denote significance at the 10%, 5%, 1% levels, respectively.
Table S.8: Employment effects of robot adoption controlling for other systems in the production process - Selection controls

<table>
<thead>
<tr>
<th></th>
<th>(1) Employment</th>
<th>(2) Labor costs share</th>
<th>(3) Low-skilled</th>
<th>(4) High-skilled</th>
<th>(5) Manufacturing employment</th>
<th>(6) Share of manuf. employment</th>
<th>(7) Average wage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Robots</strong></td>
<td>0.0436*</td>
<td>-0.0387***</td>
<td>0.0547**</td>
<td>-0.00322</td>
<td>0.0262</td>
<td>-0.00630</td>
<td>-0.00431</td>
</tr>
<tr>
<td></td>
<td>(0.0249)</td>
<td>(0.00900)</td>
<td>(0.0266)</td>
<td>(0.0533)</td>
<td>(0.0274)</td>
<td>(0.00529)</td>
<td>(0.0121)</td>
</tr>
<tr>
<td><strong>Robots</strong></td>
<td>0.0424*</td>
<td>-0.0334***</td>
<td>0.0407</td>
<td>0.0888*</td>
<td>0.0413</td>
<td>-0.00329</td>
<td>-0.0132</td>
</tr>
<tr>
<td></td>
<td>(0.0253)</td>
<td>(0.0121)</td>
<td>(0.0267)</td>
<td>(0.0490)</td>
<td>(0.0264)</td>
<td>(0.00497)</td>
<td>(0.0161)</td>
</tr>
<tr>
<td><strong>CAM</strong></td>
<td>0.0367**</td>
<td>-0.000974</td>
<td>0.0322*</td>
<td>0.0384</td>
<td>0.0277</td>
<td>-0.00311</td>
<td>0.00108</td>
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<td>(0.00745)</td>
<td>(0.0185)</td>
<td>(0.0449)</td>
<td>(0.0177)</td>
<td>(0.00312)</td>
<td>(0.00918)</td>
</tr>
<tr>
<td><strong>CAM</strong></td>
<td>0.0427</td>
<td>-0.00224</td>
<td>0.00240</td>
<td>0.0528</td>
<td>-0.000722</td>
<td>-0.00817***</td>
<td>0.0109</td>
</tr>
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<td>(0.00728)</td>
<td>(0.0190)</td>
<td>(0.0371)</td>
<td>(0.0188)</td>
<td>(0.00313)</td>
<td>(0.00935)</td>
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<tr>
<td><strong>CAD</strong></td>
<td>0.0227</td>
<td>0.0122</td>
<td>0.0221</td>
<td>0.0381</td>
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<td>0.00542</td>
<td>0.0160</td>
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<td>(0.0257)</td>
<td>(0.0532)</td>
<td>(0.0226)</td>
<td>(0.00538)</td>
<td>(0.0131)</td>
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<tr>
<td><strong>CAD</strong></td>
<td>0.0558**</td>
<td>0.00880</td>
<td>0.0506**</td>
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<td>0.0560**</td>
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<td>-0.00919</td>
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<td>(0.0219)</td>
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<td><strong>FLEX</strong></td>
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<td>(0.0219)</td>
<td>(0.00485)</td>
<td>(0.00968)</td>
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<tr>
<td>R-squared</td>
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<td>0.160</td>
<td>0.218</td>
<td>0.192</td>
<td>0.208</td>
<td>0.066</td>
<td>0.616</td>
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<td>Industry-year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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</tbody>
</table>

Notes: All dependent variables are expressed in logs except for the share of manufacturing employment. 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 $t$. Selection controls in $t-4$ are firm's deflated labor productivity (in logs), firm's deflated capital intensity (in logs), firm's deflated skill intensity (in logs), firm's deflated R&D intensity (in logs), exporter, importer and foreign ownership status. 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. Clustered standard errors are given in parentheses. *, **, *** denote significance at the 10%, 5%, 1% levels, respectively.
Table S.9: Employment effects of robot adoption controlling for other systems in the production process - Propensity score

<table>
<thead>
<tr>
<th></th>
<th>(1) Employment</th>
<th>(2) Labor costs Low-skilled share</th>
<th>(3) Low-skilled</th>
<th>(4) High-skilled</th>
<th>(5) Manufacturing employment</th>
<th>(6) Share of manuf. employment</th>
<th>(7) Average wage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Robots (_t)</td>
<td>0.0480*</td>
<td>-0.0287**</td>
<td>0.0718**</td>
<td>-0.0309</td>
<td>0.0375</td>
<td>0.0375</td>
<td>-0.00331</td>
</tr>
<tr>
<td></td>
<td>(0.0273)</td>
<td>(0.0117)</td>
<td>(0.0314)</td>
<td>(0.0591)</td>
<td>(0.0287)</td>
<td>(0.00491)</td>
<td>(0.0164)</td>
</tr>
<tr>
<td>Robots (_t-4)</td>
<td>0.0618*</td>
<td>-0.0334**</td>
<td>0.0697*</td>
<td>-0.0415</td>
<td>0.0629*</td>
<td>-0.00247</td>
<td>-0.0151</td>
</tr>
<tr>
<td></td>
<td>(0.0359)</td>
<td>(0.0151)</td>
<td>(0.0379)</td>
<td>(0.0702)</td>
<td>(0.0353)</td>
<td>(0.00550)</td>
<td>(0.0185)</td>
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<tr>
<td>CAM (_t)</td>
<td>0.0524**</td>
<td>-0.0101</td>
<td>0.0475**</td>
<td>-0.00220</td>
<td>0.0483**</td>
<td>-0.000456</td>
<td>-0.000396</td>
</tr>
<tr>
<td></td>
<td>(0.0210)</td>
<td>(0.00788)</td>
<td>(0.0229)</td>
<td>(0.0505)</td>
<td>(0.0216)</td>
<td>(0.00264)</td>
<td>(0.0103)</td>
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<tr>
<td>CAM (_t-4)</td>
<td>0.00853</td>
<td>-0.00262</td>
<td>-0.00826</td>
<td>0.0971**</td>
<td>0.00216</td>
<td>-0.00529</td>
<td>0.0210*</td>
</tr>
<tr>
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<td>(0.0194)</td>
<td>(0.00705)</td>
<td>(0.0211)</td>
<td>(0.0415)</td>
<td>(0.0191)</td>
<td>(0.00453)</td>
<td>(0.0112)</td>
</tr>
<tr>
<td>CAD (_t)</td>
<td>0.0207</td>
<td>0.0136</td>
<td>0.0225</td>
<td>-0.0352</td>
<td>0.0501**</td>
<td>0.0104</td>
<td>0.00509</td>
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<tr>
<td></td>
<td>(0.0332)</td>
<td>(0.00956)</td>
<td>(0.0342)</td>
<td>(0.0663)</td>
<td>(0.0243)</td>
<td>(0.00802)</td>
<td>(0.0149)</td>
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<tr>
<td>CAD (_t-4)</td>
<td>0.0389</td>
<td>0.0141</td>
<td>0.0312</td>
<td>0.174**</td>
<td>0.0414</td>
<td>-0.00215</td>
<td>-0.00880</td>
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<tr>
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<td>(0.0251)</td>
<td>(0.0109)</td>
<td>(0.0283)</td>
<td>(0.0695)</td>
<td>(0.0252)</td>
<td>(0.00375)</td>
<td>(0.0126)</td>
</tr>
<tr>
<td>FLEX (_t)</td>
<td>0.0129</td>
<td>0.00845</td>
<td>0.0135</td>
<td>0.113*</td>
<td>0.00224</td>
<td>-0.00982**</td>
<td>-0.00467</td>
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<tr>
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<td>(0.0226)</td>
<td>(0.00917)</td>
<td>(0.0235)</td>
<td>(0.0580)</td>
<td>(0.0236)</td>
<td>(0.00496)</td>
<td>(0.0117)</td>
</tr>
<tr>
<td>FLEX (_t-4)</td>
<td>0.00370</td>
<td>0.0197*</td>
<td>-0.00359</td>
<td>0.113**</td>
<td>0.00214</td>
<td>-0.00250</td>
<td>0.00207</td>
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<tr>
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<td>(0.0201)</td>
<td>(0.0103)</td>
<td>(0.0228)</td>
<td>(0.0569)</td>
<td>(0.0195)</td>
<td>(0.00387)</td>
<td>(0.0107)</td>
</tr>
</tbody>
</table>

Observations 4632 4595 4608 4624 4624 4595
R-squared 0.214 0.206 0.229 0.244 0.244 0.229
Industry-year fixed effects Yes Yes Yes Yes Yes Yes

Notes: All dependent variables are expressed in logs except for the share of manufacturing employment. 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 \(_t\). Selection controls in \(_t-4\) are firm’s deflated labor productivity (in logs), firm’s deflated capital intensity (in logs), firm’s deflated skill intensity (in logs), firm’s deflated R&D intensity (in logs), exporter, importer and foreign ownership status. 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. Clustered standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.