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Measuring the Technological Bias of Robot Adoption and its Implications for the Aggregate Labor Share

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Measuring the Technological Bias of Robot Adoption and its Implications for the Aggregate Labor Share*

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Abstract

This paper investigates the technological bias of robot adoption using a rich panel data set of Spanish manufacturing firms over a 25-year period. We apply the production function estimation when productivity is multidimensional to the case of an automating technology, to reveal the Hicks-neutral and labor-augmenting technological change brought about by robot adoption within firms. Our results indicate a causal effect of robots on Hicks-neutral and labor-augmenting components of productivity. The biased technological change turns out to be an important determinant of the decline in the aggregate share of labor in the Spanish manufacturing sector.

JEL codes: O33, J24, D24.

Keywords: Robots, Automation, Technological change, Productivity, Labor share.

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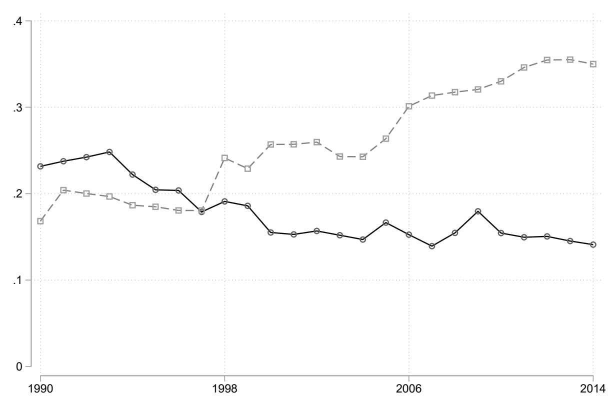
1 Introduction

The decline in the manufacturing share of labor is a common trend in most advanced economies. Many papers have investigated this phenomenon from a macroeconomic perspective emphasizing that new technologies increase the substitution of capital for labor in the production process (see Karabarbounis and Neiman, 2013; Autor et al., 2017). Recent attempts to explain this fact highlight the role of reallocation of sales and resources towards the best performing firms within industries that produce with a lower labor share due to higher markups (see De Loecker et al., 2020; Autor et al., 2020) or higher degree of automation (Hubmer and Restrepo, 2021). This paper fills an important gap in this recent debate by moving towards a firm-level perspective and answering two major research questions. First, we investigate how new technologies in form of robots are biased towards specific factors of production, thereby revealing the Hicks-neutral and labor-augmenting technological change brought about by robot adoption within firms. Second, we investigate the role of automation and the biased technological change in the decline of the aggregate share of labor in the Spanish manufacturing sector.

Figure 1: *Evolution of the Aggregate Share of Labor in Variable Costs and the Share of Firms Using Robots in Spanish Manufacturing (1990-2014)*



Notes: The figure depicts the evolution of the aggregate share of labor in variable costs (solid line) and the share of firms using robots (dashed line) in the Spanish manufacturing sector. The figure is based on an unbalanced sample of 2,399 firms between 1990 and 2014. For details on the sample construction see Section 2. We follow Doraszelski and Jaumandreu (2018) in defining the aggregate share of labor in variable costs. The numbers for their time period (1990 to 2006) are almost identical. Doraszelski and Jaumandreu (2018) also show, that these numbers correlate well with other measures of labor share, such as the wage income in GDP from official statistics.
Source: Authors' computations based on ESEE data.

A first indication on the link between automation and the decline in labor share can be seen in Figure 1. The figure plots the evolution of the aggregate share of labor and the share of firms that use robots in their production process. The figure indicates a negative relationship (the correlation coefficient is -0.77). While the share of robot firms increases from 17% in 1990 to 35% in 2014, the aggregate share of labor falls from 23% to 14% in the same time period.[1] The aim of this paper is to reveal to what extent the decline in the labor share can be attributed to automation. Is it automation per se, or is it the biased technological change that is embedded when automating the production process.

To do so, we use a panel data set of Spanish manufacturing firms from the Encuesta Sobre Estrategias (ESEE) over the period from 1990 to 2014. The data is exceptionally useful for the purposes of our research. First, it is used by Doraszelski and Jaumandreu (2018) in their production function estimation framework suited to the case of multidimensional productivity. Second, Koch et al. (2021) as well as Stapleton and Webb (2020) make use of the ESEE data to investigate the firm-level implications of robot adoption. Thus, the data set provides us with an excellent opportunity to combine these two lines of research. To identify the bias of robot adoption, we follow the strategy proposed by Doraszelski and Jaumandreu (2018) and "infer the firm's multidimensional productivity from its input usage, in particular its labor and materials decisions. The key to identifying the bias of technological change is that Hicks-neutral technological change scales input usage but, in contrast to labor-augmenting technological change, does not change the mix of inputs that a firm uses. A change in the input mix therefore contains information about the bias of technological change, provided we control for the relative prices of the various inputs and other factors that may change the input mix" (cf. Doraszelski and Jaumandreu, 2018, p.1029). Importantly, the data set and the chosen approach allow us to control for an extensive range of firm-level factors and decisions that affect the demand for inputs within firms and their decision to automate the production process. Beside a firm's R&D investment, we will focus on outsourcing practices and labor market institutions. Recent literature has shown crucial inter-dependencies between sourcing decisions and automation at the firm level (see Artuc et al., 2020; Faber, 2020; Bonfiglioli et al., 2020; Krenz et al., 2021) as well as labor market institutions and the decision to adopt robots (see Fan et al., 2021; Belloc et al., 2022). We account for these firm-level decisions using information on the share of temporary workers and the share of subcontracting to infer the effects of robots on the Hicks-neutral and labor-augmenting components of the multidimensional productivity.

In a first step, we apply our structural production function estimates to uncover how the overall productivity along with its Hicks-neutral and labor-augmenting components evolve in the Spanish manufacturing sector and how the adoption of robots affects the individual productivity processes. We find that total factor productivity (TFP) declined in Spain up until the financial crisis by about 6% and only started to catch up afterwards. The dismal performance of productivity growth between 1995 and 2007 is thoroughly documented in García-Santana et al. (2020). We extend their findings and reveal that the decline in TFP is to a large extent caused by firms that do no adopt robots (non-adopters). Moreover, a primary source of the decline is the fall in Hicks-neutral productivity rather than labor-augmenting technological change. This supports the conclusion in García-Santana et al. (2020) that the aggregate productivity in Spain stagnated due to the *(unbiased)* misallocation of production factors across firms. By moving towards the firm-level perspective, we show that the

[1] A similar pattern is revealed when the same graphical analysis is repeated for ten different manufacturing industries (see Figure A.1 in the Online Appendix).

adoption of robots has a significant and sizable impact on the aggregate productivity, and, in similar magnitudes, on its Hicks-neutral and labor-augmenting components. In other words, automation shifts the common TFP but is at the same time biased towards specific factors. Interestingly, our estimates reveal that the productivity effect from robot adoption depends on the firms' initial productivity level, indicating that the productivity gains are higher when firms are already very productive, but this additional gain is declining in the productivity of the firm leading to satiation at high levels of productivity.

In a second step, we investigate if the decline in the labor share can be attributed to the adoption of robots. In the short-run perspective, our estimates reveal that automation does not reduce the labor share within firms, once controlling for the technological bias of robot adoption. The latter turns out to be the main driver for the decline in the labor share. Specifically, a 10% increase in the labor-augmenting productivity reduces the labor share by around 0.3 percentage points. When studying the long-run changes, we use a long-difference regression approach to exploit variation across firms in the pre-determined level of robot adoption and in long-run changes in the labor share. The results again suggest that robots affect only labor-augmenting productivity in the long run, while labor share changes cannot be explained by the use of robots. We furthermore show that it is the base levels of labor share that to a large extent can explain long-term changes in the labor-augmenting and Hicks-neutral components of productivity.

Our study speaks to the literature on the impact of robots. Inspired by the aggregate industry-level analysis as in Graetz and Michaels (2018); Acemoglu and Restrepo (2020) or Dauth et al. (2018), there are now several studies available that investigate the impact of robots on firm-level outcomes. These include, among others, Humlum (2019); Acemoglu et al. (2020) or Koch et al. (2021). One major problem in these studies is that it is not always possible to identify a *causal* effect of automation given the specific setting. Therefore, recent approaches turn to the shift-share instrument design (see Bonfiglioli et al., 2020; Aghion et al., 2019; Bessen et al., 2020). In our paper, we use a different strategy by following the approach proposed in the production function estimation literature to account for causal affects of R&D, exports and other firm activities on the firm-level productivity (see, for example Doraszelski and Jaumandreu, 2013; De Loecker, 2013; Aw et al., 2011).

We furthermore contribute to the literature on the decline in the aggregate labor share. Recent papers exploiting the firm-level perspective emphasize the role of reallocation of sales and resources towards the best performing firms, producing with a lower labor share, which can arise due to higher markups (see De Loecker et al., 2020; Autor et al., 2020) or a higher degree of automation (Hubmer and Restrepo, 2021). Our findings are connected to these results. On the one hand, we show that the technological bias of robot adoption can explain a decline in the labor share within firms. On the other hand, looking at the long run, our findings reveal that the base levels of labor share can to a large extent explain long-term changes in the labor-augmenting and Hicks-neutral components of productivity. Since these firms have larger market shares, it therefore confirms the importance of the reallocation towards firms with lower labor costs in explaining the overall decline in the aggregate labor share.

We also contribute to the literature on the estimation of production functions. Our point of departure is the recent work by Doraszelski and Jaumandreu (2018), who investigate the bias of technological change at the firm level by measuring how much of it is labor-augmenting and how much is factor-neutral.[2] While their focus is on R&D, we extend and adjust the framework, to reveal the impact of robots on the different productivity processes within firms. By doing so, we are the first to provide causal evidence on the specific role of robots in shaping factor demand within firms by shifting the productivity evolution of different factors in a biased way.

The reminder of the paper is organized as follows. In Section 2 we describe our data-set used in the structural estimation that is described in Section 3. Section 4 presents the impact of automation on multidimensional productivity and the labor share. Section 5 concludes.

2 Data

Our empirical analysis is based on data collected by Encuesta Sobre Estrategias Empresariales (ESEE) 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 on firms and a high degree of representativeness for the manufacturing sector at large. While one can distinguish between 20 different industries at the two-digit level of the NACE Rev. 2 classification, we will aggregate the industries into ten broader manufacturing sectors.[3] 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). A crucial input to our study is a firm-level indicator on robot usage. Furthermore, we make use of extensive information about firms' outsourcing activities and employment conditions.

To identify whether a firm is a robot adopter or not, we use a quadrennial variable available from 1990. Specifically, the survey asks firms: "State whether the production process uses any of the following systems: 1. Computer-digital machine tools; 2. Robotics; 3. Computer-assisted design; 4. Combination of some of the above systems through a central computer (CAM, flexible manufacturing systems, etc.); 5. Local Area Network (LAN) in manufacturing activity." Based on this question, we construct a 0/1 robot indicator variable equal to one if the firm uses robots and zero otherwise. As it is shown in Koch et al. (2021), this variable comes along with hikes in investments in machinery, in the years around the adoption of robots, as well as other variables such as process innovation and innovations in organizational methods, and thus provides reliable information on the automation decision within firms.[4]

[2]Unlike Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015), the selected procedure applies parametric instead of non-parametric inversion of the input demand function to recover unobserved productivity measures.

[3]The aggregation follows Doraszelski and Jaumandreu (2018). We do so to have enough variation in robot adoption across firms, which is crucial for the estimation strategy. A concordance table is provided in the Online Appendix, see Table A.1.

[4]To come up with a yearly panel variable, we fill in the missing years between the complete survey years, thereby assuming that a firm using (or not) robots in a given year will continue doing so throughout the four-year period until

We measure output as value added (production value minus the value sum of energy purchases, raw materials and services), suitably deflated with a combined firm-level output and intermediate input price index available in our data. Labor input is calculated as total hours worked, where we multiply the number of workers by the average hours per worker. In turn, average hours represent normal hours plus overtime minus time lost at the workplace. Value of intermediate goods consumption (including raw materials, components, energy, and services) is our preferred measure of material inputs. Capital stock is computed from investments using the perpetual inventory method and deflated using an industry-level price index. The share of temporary workers and share of subcontracting are two key components of our estimation, as they allow to account for quality differences in labor and material inputs across firms. The share of temporary workers is computed from the average number of temporary workers and average total employment in a firm in a given year. The share of subcontracting represents the share of work carried out by other companies (subcontractors) in terms of material inputs supply. Finally, the average wage is defined as the firm's labor costs divided by the total number of workers. Export share is the share of export sales in total sales. R&D is the amount of resources devoted to R&D activities (costs of personnel and equipment appropriately deflated). Investments in machinery equipment account for purchases and major repairs of technical facilities, machinery and tools performed in a given year (share of total investment).

When it comes to the construction of the final sample, we aim to keep as many firms in our analysis as possible. First, for each firm we select the years when it is active in the survey. Next, we exclude the firms undergoing major changes in corporate structure from the sample (primarily mergers). Finally, we drop observations where any of our variables of interest is missing. Specifically, we follow Doraszelski and Jaumandreu (2018) and remove observations without temporary workers. We also restrict the sample to firms with at least three years of consecutive data because we are going to rely on lags in our identification. The constructed sample consists of 2,399 unique firms with seven years of observations per firm on average.[5]

3 Structural estimation

Our estimation strategy relies on the approach suggested by Doraszelski and Jaumandreu (2018) and is adapted to the case of robot technology. It stems from the literature on structural methods of productivity estimation but allows for higher flexibility when estimating parameters of the input demand functions. They show that the key to disentangling labor-augmenting and Hicks-neutral productivity is in allowing for quality differences between different types of labor and different types of materials. In our data set, such proxies are the share of temporary workers (S_T) and the share of outsourced materials (S_O).

The starting point is a CES production function of a firm i in time period t, which takes the

the question is asked again.

[5]Summary statistics for the group of robot and non-robot firms are provided in Online Appendix Table A.2. The distribution of firms and observations across industries is available in Table A.3 in the Online Appendix.

following form:

$$Y_{it} = \exp(\omega_{H,it}) \exp(e_{it}) \left[\beta_K K_{it}^{-\frac{1-\sigma}{\sigma}} + (\exp(\omega_{L,it}) L_{it})^{-\frac{1-\sigma}{\sigma}} + \beta_M M_{it}^{-\frac{1-\sigma}{\sigma}} \right]^{-\frac{\nu\sigma}{1-\sigma}}, \tag{1}$$

where Y_{it} stands for the output of the firm, K_{it} is capital, L_{it} is an aggregate of permanent and temporary labor, M_{it} is an aggregate of in-house and outsourced materials, and labor-augmenting and Hicks-neutral productivities are denoted by $\omega_{L,it}$ and $\omega_{H,it}$, respectively.[6,7] The firm also receives a random shock e_{it}, which is mean zero and uncorrelated over time and across firms. Parameters to be estimated are the elasticity of substitution (σ), the elasticity of scale (ν), and the elasticity of capital ($\beta_K = 1 - \beta_M$).

The multidimensional productivity follows an endogenous first-order Markov process, where next period productivity measures are probabilistically determined by previous period productivity and automation technology measures. Specifically, we assume:

$$\omega_{L,it+1} = E_t \left[\omega_{L,it+1} | \omega_{L,it}, \text{Robots}_{it} \right] + \xi_{L,it+1} = g_{L,t}(\omega_{L,it}, \text{Robots}_{it}) + \xi_{L,it+1}, \tag{2}$$

$$\omega_{H,it+1} = E_t \left[\omega_{H,it+1} | \omega_{H,it}, \text{Robots}_{it} \right] + \xi_{H,it+1} = g_{H,t}(\omega_{H,it}, \text{Robots}_{it}) + \xi_{H,it+1}. \tag{3}$$

Conditional expectation functions $g_{L,t}(\cdot)$ and $g_{H,t}(\cdot)$ capture potential non-linearities in the productivity process and are estimated non-parametrically. The random shocks $\xi_{L,it+1}$ and $\xi_{H,it+1}$ arrive after a firm has optimally decided on the use of robots and, thus, are not correlated with random shocks to the output (e_{it}). To account for the intensive margin of robot use in the productivity process, we use investments in machinery equipment. As shown in Koch et al. (2021), the adoption of robots is associated with an increase in investments in machinery equipment, which we denote by Q_{it}. By doing so, we are able to differentiate not only between robot adopters and non-adopters, but also between robot adopters of different types depending on how much they were willing to invest in these machines.

On the demand side, we assume that firms have market power on the differentiated final goods varieties. The inverse residual demand function of a firm $P(Y_{it}, D_{it})$ depends on its output Y_{it} and the demand shifter D_{it}. When taking model to the data, we use export participation as an approximation for the firm-level demand shifter. On input markets, firms act as price takers. More formally, each firm faces a certain level of wages (W_{it}) and a certain level of intermediate input prices ($P_{M,it}$). Solving the dynamic problem of the firm, Doraszelski and Jaumandreu (2018) demonstrate

[6] Such production function follows the task based approach of automation, as in Acemoglu and Restrepo (2018), where output is a composite of different tasks combined in a constant elasticity of substitution (CES) aggregate.

[7] Capital follows the law of motion from Olley and Pakes (1996), where the choice of current period investment is equivalent to the choice of next period capital stock. Furthermore, we follow Doraszelski and Jaumandreu (2018), in defining the aggregate functions for labor and materials, such that it accommodates for differences in the productivities of permanent and temporary labor, as well as in-house and outsourced materials. More specifically, permanent labor and outsourced materials in the model are subject to convex adjustment costs, while temporary labor and in-house materials are static inputs.

that the residual demand the firm faces can be represented by the following equation:

$$X_{it} = \beta_K K_{it}^{-\frac{1-\sigma}{\sigma}} + \beta_M \left[M_{it} \exp(\gamma_1(S_{O,it}))\right]^{-\frac{1-\sigma}{\sigma}} \left[\frac{S_{L,it}}{1-S_{L,it}} \lambda_1(S_{T,it}) + 1\right], \tag{4}$$

where $S_{L,it} = W_{it}L_{it}/(W_{it}L_{it} + P_{M,it}M_{it})$ is the share of labor in variable cost. The unknown functions $\lambda_1(S_{T,it})$ and $\gamma_1(S_{O,it})$ are to be estimated non-parametrically. They can be interpreted as correction terms accounting for heterogeneity across firms based on the quality of labor and material mix they use in the production process. Importantly, the potential of a firm to hire and fire workers as well as its ability to outsource materials have direct implications for its robot adoption decisions. Thus, by using information on the share of temporary workers and the share of subcontracting, the methodology allows us to capture the effects from robot adoption on productivity in a more consistent and robust way.

Accordingly, labor-augmenting productivity can be recovered through the following equation, where low-case variables represent log measures:

$$\begin{aligned}(1-\sigma)\omega_{L,it} &= -\sigma \ln(1-\beta_K) + m_{it} - l_{it} + \sigma(p_{M,it} - w_{it}) - \sigma\lambda_2(S_{T,it}) + (1-\sigma)\gamma_1(S_{O,it}) \\ &\equiv h_L(m_{it} - l_{it}, p_{M,it} - w_{it}, S_{T,it}, S_{O,it}),\end{aligned} \tag{5}$$

where $\lambda_2(S_{T,it})$ is another correction term to be estimated non-parametrically.

In a similar fashion, Hicks-neutral productivity can be characterized by the following equality:

$$\begin{aligned}\omega_{H,it} =& -\ln(\nu(1-\beta_K)E_t[\exp(e_{it})]) + \frac{1}{\sigma} m_{it} + p_{M,it} - p_{it} - \ln\left(1 - \frac{1}{\eta(p_{it}, D_{it})}\right) \\ &+ \left(1 + \frac{\nu\sigma}{1-\sigma}\right) x_{it} + \frac{1-\sigma}{\sigma}\gamma_1(S_{O,it}) \\ \equiv& h_H(k_{it}, m_{it}, S_{L,it}, p_{it}, p_{M,it}, D_{it}, S_{T,it}, S_{O,it}),\end{aligned} \tag{6}$$

where $\eta(p_{it}, D_{it})$ is the absolute value of the residual demand price elasticity.[8]

Then, the estimation equations are derived by substituting productivity laws of motion (2)–(3) into equations (5)–(6). In what follows, we will describe the resulting estimation equations and specific adjustments we make to account for robot adoption decisions. Here it is important to highlight that even though the identification of R&D effects on productivity is not our primary concern, we still keep this variable as an additional control across all estimations. Hence, we aim to recover productivity changes caused by robots after controlling for R&D as one of the major drivers of productivity.

The first equation to be estimated is expressed as follows:

$$\begin{aligned}m_{it} - l_{it} =& -\sigma(p_{M,it} - w_{it}) + \sigma\lambda_2(S_{T,it}) - (1-\sigma)\gamma_1(S_{O,it}) \\ &+ (1-\sigma) g_{L,t-1}\left(\frac{1}{1-\sigma} h_L(m_{it-1} - l_{it-1}, p_{M,it-1} - w_{it-1}, S_{T,it-1}, S_{O,it-1}), \text{Robots}_{it-1}\right)\end{aligned}$$

[8] In practice, we approximate $\eta(p_{it}, D_{it})$, $\lambda_1(S_{T,it})$, $\lambda_2(S_{T,it})$, and $\gamma_1(S_{O,it})$ with third-order polynomials.

$$+ (1-\sigma)\xi_{L,it}. \tag{7}$$

Further, we allow $g_{L,t-1}\left(\frac{h_L(\cdot)}{1-\sigma}, \text{Robots}_{it-1}\right)$ to differ between observations with and without robots:

$$\begin{aligned} g_{L,t-1}\left(\frac{h_L(\cdot)}{1-\sigma}, \text{Robots}_{it-1}\right) =& g_{L0}(t-1) + \mathbb{1}(\text{Robots}_{it-1}=0) g_{L1}\left(\frac{h_L(\cdot)}{1-\sigma}\right) \\ &+ \mathbb{1}(\text{Robots}_{it-1}=1) g_{L2}\left(\frac{h_L(\cdot)}{1-\sigma}, Q_{it-1}\right). \end{aligned} \tag{8}$$

Thereby, Q_{it-1} represents previous period investments in machinery equipment. Functions $g_{L1}\left(\frac{h_L(\cdot)}{1-\sigma}\right)$ and $g_{L2}\left(\frac{h_L(\cdot)}{1-\sigma}, Q_{it-1}\right)$ are approximated by complete sets of third-order polynomials. We follow Doraszelski and Jaumandreu (2018) and base the estimation on the moment conditions:

$$E[A_{L,it}(z_{it})(1-\sigma)\xi_{L,it}] = 0, \tag{9}$$

where $A_{L,it}(z_{it})$ is a vector of instruments (functions of the exogenous variables z_{it}).[9] Specifically, the instruments for the equation (7) include a constant, time fixed effects, complete set of polynomials in (m_{it-1}, l_{it-1}, $(p_{M,it} - w_{it})$) interacted with a lagged non-adopter indicator, lagged robot indicator, complete set of polynomials in (m_{it-1}, l_{it-1}, $(p_{M,it} - w_{it})$, Q_{it-1}) interacted with a lagged adopter indicator, polynomial in the amount of outsourced materials used in the production process ($M_{it-1}S_{O,it-1}$), contemporaneous robot usage indicator, lagged R&D expenditures, and a demand shifter.

The second estimation equation takes the following form:

$$\begin{aligned} y_{it} =& -\frac{\nu\sigma}{1-\sigma} x_{it} + g_{H,t-1}(h_H(k_{it-1}, m_{it-1}, S_{L,it-1}, p_{it-1}, p_{M,it-1}, D_{it-1}, S_{T,it-1}, S_{O,it-1}), \text{Robots}_{it-1}) \\ &+ \xi_{H,it} + e_{it}. \end{aligned} \tag{10}$$

Again, we allow $g_{H,t-1}(h_H(\cdot), \text{Robots}_{it-1})$ to differ between observations with and without robots utilizing the heterogeneity across firms in the level of investments in machinery equipment (Q_{it-1}). The moment conditions are specified accordingly:

$$E[A_{H,it}(z_{it})(\xi_{H,it} + e_{it})] = 0. \tag{11}$$

The instruments in the estimation of the equation (10) include a constant, time fixed effects, lagged robot indicator, polynomial in $(p_{M,it-1} - p_{it-1})$, polynomial in p_{it-1}, complete set of polynomials in ($M_{it-1}S_{L,it-1}/(1-S_{L,it-1})$,$K_{it-1}$) interacted with a lagged non-adopter indicator, complete set of polynomials in ($M_{it-1}S_{L,it-1}/(1-S_{L,it-1})$,$K_{it-1}$) interacted with a lagged adopter indicator, polynomial in the amount of outsourced materials used in the production process ($M_{it-1}S_{O,it-1}$), previous period investments in machinery equipment, and lagged R&D expenditures.

[9] When considering instruments we make sure that they are not correlated with $(1-\sigma)\xi_{L,it}$. At the same time, there are no restrictions on them being potentially correlated with $\omega_{L,it}$. That is why we prefer to use lagged variables.

First, we recover σ, $\lambda_2(S_{T,it})$, and $\gamma_1(S_{O,it})$ by estimating the equation (7) with a standard Hansen (1982) two-step GMM estimator. Then, we plug the necessary parameters into the equation (10) and estimate ν, β_K, $\eta(p_{it}, D_{it})$, and $\lambda_1(S_{T,it})$ in a similar two-step GMM procedure. Our final estimates of the production function parameters are to a large extent in line with the results presented in Doraszelski and Jaumandreu (2018) and we therefore present results of this exercise in Table A.3 in the Online Appendix.

4 Robots, technological change, and the labor share

This section uses the structural estimates in a first step to reveal how the overall productivity and its Hicks-neutral and labor-augmenting components evolve in the Spanish manufacturing sector and how the adoption of robots affects the individual productivity processes. In a second step, we investigate if the decline in the labor share can be attributed to the adoption of robots.

4.1 Robots and multidimensional productivity

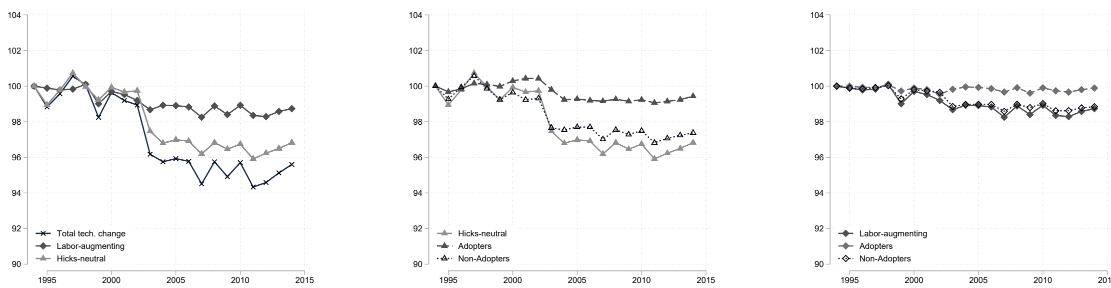
We begin with a graphical illustration of our estimates of multidimensional productivity. The left panel in Figure 2 illustrates the evolution of total factor productivity and its Hicks-neutral and labor-augmenting components in Spanish manufacturing across the years 1995 to 2014, thereby revealing two main patterns. First, TFP declined in Spain up until the financial crisis by about 6% and only started to catch up afterwards. Second, we reveal that the decline in TFP is to a large extent based on the fall in Hicks-neutral productivity and only to a small extent based on the evolution in labor-augmenting technological change. Noteworthy, the size of our estimates is in line with the estimates in García-Santana et al. (2020), who report an annual TFP growth of -0.7% during these years based on aggregate data from EU KLEMS. Furthermore, our finding that the decline in TFP is mainly due to a fall in Hicks-neutral productivity, supports the conclusion in García-Santana et al. (2020) that aggregate productivity in Spain stagnated due to the *(unbiased)* misallocation of production factors across firms.

The middle and right panel in Figure 2 re-plot the Hicks-neutral and labor-augmenting productivity, respectively, and differentiate between the group of robot adopters and non-adopters. This reveals that the decline in productivity in Spanish manufacturing rests on the shoulders of firms that do not adopt robots in their production process. Notably, robot adopting firms only see a slight decline in their Hicks-neutral productivity (of about 1%) while keeping their labor-augmenting productivity at a stable level compared to non-adopters, despite the increase in misallocation of production factors in Spain during this period (see García-Santana et al., 2020).[10]

We now estimate the productivity effects of robots, both on aggregate productivity as well as its Hicks-neutral and labor-augmenting components. To estimate the endogenous productivity

[10]In Online Appendix A.5 we provide a brief comparison of mean productivity levels and growth rates for observations with and without robots.

Figure 2: *Evolution of Hicks-neutral and Labor-augmenting Productivity in Spanish Manufacturing*



Notes: The left panel illustrates the evolution of TFP for the Spanish manufacturing sector at large (solid black line with x), and its Hicks-neutral (light-gray with triangle) and labor-augmenting (dark-gray with diamonds) components for the years 1995 to 2014. The middle and right panel replots the Hicks-neutral (light-gray with triangle) and labor-augmenting (dark-gray with diamonds) productivity respectively, and differentiates between the group of robot adopters (dashed line with filled triangles/diamonds) and non-adopters (dotted line with hollow triangles/diamonds). In each panel TFP and its components is normalized to 100 in the year 1994.
Source: Authors' computations based on ESEE data.

Table 1: Estimates of Multidimensional Productivity and Robots

	Total ($\omega_{T,t}$)	labor-augmenting ($\omega_{L,t}$)	Hicks-neutral ($\omega_{H,t}$)
Robots$_{t-1}$	0.175***	0.0854***	0.0758**
	(0.0588)	(0.0217)	(0.0345)
Productivity$_{t-1}$	0.918***	0.901***	0.904***
	(0.00499)	(0.00596)	(0.00517)
Productivity$^2_{t-1}$	0.00246***	-0.00330**	0.00280***
	(0.000118)	(0.00139)	(0.000123)
Productivity$_{t-1}$ × Robots$_{t-1}$	0.0647**	0.110***	0.0426
	(0.0303)	(0.0171)	(0.0378)
Productivity$^2_{t-1}$ × Robots$_{t-1}$	-0.0197***	-0.0361***	-0.00605
	(0.00352)	(0.00325)	(0.0157)
Productivity$_{t-1}$ × Productivity$^2_{t-1}$ × Robots$_{t-1}$	0.0000106	-0.000757***	0.0000143
	(0.000143)	(0.0000986)	(0.00148)
Observations	8770	8770	8770
R-squared	0.841	0.854	0.809

Notes: Estimates are obtained after running the estimation procedure on multidimensional productivity as described in Section 3 on the data and using the specification of the productivity process given by equation (12). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' computations based on ESEE data.

process, we follow existing work (e.g., De Loecker, 2013), use our productivity estimates and rely on a second-order polynomial in productivity while interacting all terms with our robot dummy variable to estimate the laws of motion as specified in equation (2) and (3).[11] Formally, we rely on

$$\omega_{P,it+1} = \text{Robots}_{it} + \sum_{j=1}^{2} \alpha_j \omega_{P,it}^{j} + \sum_{j=1}^{2} \beta_j \left(\omega_{P,it}^{j} \times \text{Robots}_{it}\right) + \gamma \omega_{P,it} \times \omega_{P,it}^{2} \times \text{Robots}_{it} + \xi_{P,it+1}, \tag{12}$$

with subscript P is either T (total), L (labor-augmenting), or H (Hicks-neutral). Estimates of the coefficients (α, β and γ) are reported in Table 1. The second line of the table reveals persistence in productivity of around 90% from year to year. This high persistence is similar to estimates reported in other studies, e.g., De Loecker (2013) for the Slovenian manufacturing sector. Looking at the first line in Table 1 shows that the adoption of robots has a significant and sizable impact on aggregate productivity, and, in similar magnitudes, on the Hicks-neutral and labor-augmenting components. At the same time, the estimates for second-order polynomials and its interaction terms with robots indicate an inverse U-shaped relationship for the aggregate productivity and the labor-augmenting productivity process. Estimates in line four demonstrate that the productivity effect from robot adoption depends on the firm's initial productivity level, which means that the productivity gains are higher when firms are already very productive. However, as evident from looking at the last lines in Table 1, this additional gain is declining in the productivity of the firm leading to satiation at high levels of productivity.

4.2 Implications for the labor share

Now we use the firm-level estimates of aggregate productivity and its components to reveal how robots and changes in productivity affect a firm's labor share. As it is evident from our production function in equation (1) and the discussion in Section 3, one would expect labor-augmenting productivity growth to contribute to the decline of the labor share, while changes in Hicks-neutral productivity should leave the labor share unaffected. Furthermore, if the adoption of robots and its productivity gains are correctly estimated in our structural framework, then the adoption of robots should not affect the labor share, as biased technological change in robot adoption is already captured by the labor-augmenting productivity process. To investigate this we regress the labor share and its growth rate on labor-augmenting and Hicks-neutral productivity, our indicator variable for robots, and interaction terms across all three variables, i.e.,[12]

$$\begin{aligned}\text{outcome}_{it} =& \mu_i + \gamma_1 \omega_{L,it} + \gamma_2 \omega_{H,it} + \gamma_3 \text{Robots}_{it} + \gamma_4 \omega_{L,it} \times \omega_{H,it} + \gamma_5 \omega_{L,it} \times \text{Robots}_{it} \\ &+ \gamma_6 \omega_{H,it} \times \text{Robots}_{it} + \gamma_7 \omega_{L,it} \times \omega_{H,it} \times \text{Robots}_{it} + \mu_{st} + \boldsymbol{\beta} \mathbf{X}_{it} + \epsilon_{it}\end{aligned}$$

[11] We have verified that our estimates are robust to specifications with third-order polynomials (or higher) in productivity (see Online Appendix A.6).

[12] We have also tested specifications where the right-hand side variables are lagged by one period. This does not change the insights.

Columns (1) and (5) in Table 2 report estimates of $\gamma_1 - \gamma_7$ for the labor share levels and its growth rates, respectively. In columns (2) and (6) we add industry-year fixed effects μ_{st} to capture general time trends and industry shocks that affect all firms equally within industries. In columns (3) and (7) we add controls to account for robot adoption based not only on time-invariant (μ_i) but also on time-varying firm-level variables $\boldsymbol{\beta}\mathbf{X}_{it}$. Here we include capital intensity, skill intensity, R&D intensity (all in logs), as well as indicator variables for exporting, importing, and foreign ownership. Finally, in columns (4) and (8) we combine the firm fixed effects approach with a propensity score reweighting estimator. To obtain the propensity scores, we follow the same methodology as in Koch et al. (2021) and run probit regressions for robot adoption (the treatment) on one-year lags of sales, sales growth, labor productivity, labor productivity growth, capital-, skill- and R&D-intensity, indicators for exporter, importer and foreign ownership, and year dummies.

It is important to highlight that we prefer the regression specification because we cannot fully account for the non-random selection into (and out of) robot adoption in our structural model given its design. Namely, conditional expectation functions $g_{L,t}(\cdot)$ and $g_{H,t}(\cdot)$ cannot rationalize the switches in and out of robot adoption throughout consecutive periods of time. Since we do not want to exclude such observations from the analysis, we rely on selection controls and propensity score reweighting.

Table 2: Robots, Technological Change, and Labor Share in the Short Run

	labor share				Δ labor Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\omega_{L,t}$	-0.0308***	-0.0318***	-0.0313***	-0.0336***	-0.0303***	-0.0302***	-0.0300***	-0.0291***
	(0.00257)	(0.00242)	(0.00243)	(0.00340)	(0.00227)	(0.00219)	(0.00221)	(0.00262)
$\omega_{H,t}$	-0.0113***	-0.00994***	-0.0112**	-0.00748**	-0.00596**	-0.00582**	-0.00631**	-0.00356**
	(0.00417)	(0.00367)	(0.00453)	(0.00363)	(0.00268)	(0.00240)	(0.00283)	(0.00177)
Robots$_t$	-0.00884	-0.0118**	-0.0108*	-0.0159	-0.00452	-0.00758	-0.00672	-0.0150
	(0.00604)	(0.00564)	(0.00554)	(0.0112)	(0.00589)	(0.00547)	(0.00554)	(0.00948)
$\omega_{L,t} \times \omega_{H,t}$	-0.00145***	-0.00128***	-0.00143***	-0.000260	-0.000845**	-0.000822***	-0.000883**	-0.000504
	(0.000508)	(0.000448)	(0.000554)	(0.00126)	(0.000332)	(0.000298)	(0.000349)	(0.00125)
$\omega_{L,t}\times$ Robots$_t$	0.00241	0.00463	0.00501	0.00811	-0.000441	0.00163	0.00131	0.00561
	(0.00391)	(0.00363)	(0.00360)	(0.00638)	(0.00437)	(0.00388)	(0.00394)	(0.00612)
$\omega_{H,t}\times$ Robots$_t$	-0.00960***	-0.00768***	-0.00814***	-0.00668**	-0.00499**	-0.00482**	-0.00501**	-0.00371
	(0.00259)	(0.00244)	(0.00248)	(0.00324)	(0.00207)	(0.00195)	(0.00199)	(0.00310)
$\omega_{L,t} \times \omega_{H,t}\times$ Robots$_t$	0.00957***	0.00921***	0.00904***	0.00847***	0.0115***	0.0107***	0.0108***	0.00962***
	(0.00177)	(0.00162)	(0.00163)	(0.00233)	(0.00162)	(0.00149)	(0.00152)	(0.00234)
Industry-Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Selection controls	No	No	Yes	No	No	No	Yes	No
Propensity scores	No	No	No	Yes	No	No	No	Yes
Observations	10861	10861	10770	8595	10857	10857	10766	8593
R-squared	0.170	0.265	0.278	0.277	0.124	0.190	0.193	0.229

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' computations based on ESEE data.

Estimates reported in Table 2 reveal two important insights. First, throughout all specifications, it is evident that the adoption of robots does not reduce the labor share within firms. The coefficient on robots is negative, but almost in all cases, not statistically different from zero. Second, looking at the estimates for γ_1 reveals that an increase in labor-augmenting productivity reduces the labor share. The coefficients are significant at the one-percent level and reveal that a 10% increase in labor-augmenting productivity reduces the labor share by around 0.3 percentage points. When looking at Hick-neutral productivity, one might be first surprised by its negative impact on the labor share. However, the coefficient is less precisely estimated and only significant at the 5% level in the preferred specifications that control for non-random selection into robot adoption. Furthermore, the size of the coefficient is smaller by a factor of around five or more compared to estimates for labor-augmenting productivity. For instance, the coefficient from column (8) shows that a 10% increase in Hick-neutral productivity reduces the labor share by 0.04 percentage points, while the same increase in labor-augmenting productivity would reduce the labor share by almost 0.3 percentage points.

Overall, the estimates suggest that the firms using robots have experienced a decline in labor share to begin with. Automation technology in itself does not contribute to this trend. Nevertheless, as the firm increases its productivity (primarily labor-augmenting), the labor share starts to decline. While there are many factors affecting productivity (R&D, learning from exporting, etc.), automation technology is also one of them. The evidence combined with the quantification of the productivity process from Table 1 implies that the firms most exposed to this effect are the small and less productive ones. Namely, if a relatively low-productive firm adopts a robot in current period, it would increase its labor-augmenting productivity contributing to the decline of labor share in the future. In contrast, if a relatively high-productive firm adopts a robot, it would have lower effect on its labor-augmenting productivity, hence, potentially having less significant implications for the labor share.

4.3 Long-run outcomes

Clearly, the adoption of robots and changes in the labor share might not be well captured when looking at the short-run changes. Therefore, we also explore the long-run changes in the variables of interest, i.e., labor-augmenting and Hicks-neutral components of productivity as well as the labor share. We use the long-difference regression approach and construct a cross-section, where each observation represents a single firm. Since firms have different time spans in the sample, the outcome variables are computed as annualized changes. For instance, an annualized change in labor share for a firm between its first and last period in the sample is the average one-year change in labor share through the whole period.

When it comes to the explanatory variables, we first create a variable measuring robot intensity of each firm. It expresses the total number of periods with robots in relation to the longevity of a firm in the sample. Suppose that a firm i is observed through T consecutive periods in the sample. Then, the robot intensity will be measured according to the following equation:

$$\text{Robots}_i = \frac{\sum_t^T \mathbb{1}(\text{Robots}_{it} = 1)}{T}. \tag{13}$$

Further, we use the value of an outcome variable in its base year (firm-specific) as an explanatory variable. It allows us to account for differences in levels and pre-existing trends. Similarly, in some specifications we use controls for non-random selection into robot adoption using the values of controls in the same base year. Finally, we use industry fixed effects across all specifications. Thereby we account for the shared dynamics and potential shocks common to all firms within an industry. Formally, we rely on the following estimation equation:

$$\frac{\text{outcome}_{iT} - \text{outcome}_{i0}}{T} = \beta_0 + \beta_1 \text{Robots}_i + \beta_2 \text{outcome}_{i0} + \boldsymbol{\gamma} \mathbf{X}_{i0} + \mu_s + \epsilon_i, \tag{14}$$

where β_0 is a constant, $\mathbf{X}_{i0}$ is a vector of selection controls, and μ_s are industry fixed effects. Results are presented in Table 3.

Table 3: Robots, Technological Change, and labor Share in the Long Run

	Δ labor share		Δ labor-augmenting		Δ Hicks-neutral	
	(1)	(2)	(3)	(4)	(5)	(6)
Robots	-0.0105***	-0.00376	0.607***	0.428**	0.0684*	0.0923**
	(0.00287)	(0.00303)	(0.164)	(0.175)	(0.0405)	(0.0436)
Base of dependent	-0.0269***	-0.0332***	-0.0506***	-0.0515***	-0.0731***	-0.0774***
	(0.00243)	(0.00262)	(0.00342)	(0.00354)	(0.00235)	(0.00257)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Selection controls	No	Yes	No	Yes	No	Yes
Observations	2399	2376	2399	2376	2399	2376
R-squared	0.056	0.079	0.151	0.157	0.338	0.344

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cross-section, number of observations is the number of firms.
Source: Authors' computations based on ESEE data.

The results suggest that robots affect only labor-augmenting productivity in the long run. labor share changes cannot be explained by the use of robots. In a similar fashion, the effects on Hicks-neutral productivity are not that much different from zero. Moreover, we capture a long-term declining trend in all variables. To shed more light on these processes, we estimate an alternative specification with base values of labor share, labor-augmenting and Hicks-neutral components of productivity on the right-hand side of the estimation equation at the same time. Results are reported in the Online Appendix A.7. It can be inferred from the estimates that the long-term decline in the labor share can only be explained by a pre-existing trend. The levels of labor-augmenting and Hick-neutral productivity as well as robots all fail to explain the changes in the labor share. Interestingly, it is the base levels of labor share that to a large extent can explain long-term changes in the labor-augmenting and Hicks-neutral components of productivity.

5 Conclusion

In this paper we have applied a structural productivity estimation framework adjusted for the case of multidimensional productivity with robots in order to measure the bias of technological change and explore the link between automation and the labor share decline in manufacturing. We do not find any strong evidence supporting the hypothesis existing in the literature that robots cause the labor share to decline, neither in the short run, nor in the long run. If anything, then robots contribute to the decline of labor share in manufacturing indirectly by affecting labor-augmenting and Hicks-neutral components of productivity. Labor-augmenting productivity turns out to be the main contributor to the labor share decline though.

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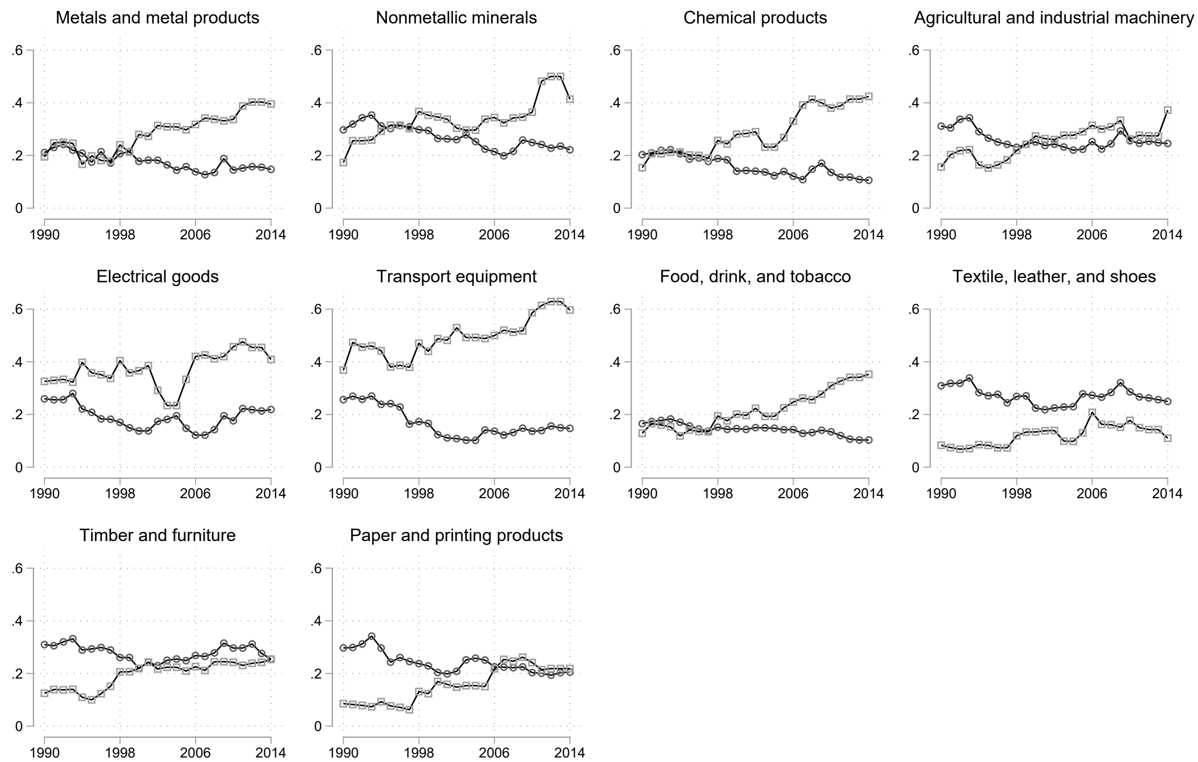
A Online Appendix

A.1 Aggregate labor share and robot adoption dynamics

Figure A.1: *Evolution of Aggregate Share of labor in Variable Costs and Share of Firms using Robots in Spanish Manufacturing Industries (1990-2014)*



Notes: The figure depicts the evolution of the aggregate share of labor in variable costs (line with hollow circles) and the share of firms using robots (line with hollow squares) in 10 Spanish manufacturing industries. The figure is based on an unbalanced sample of 2,399 firms from 1990-2014. For details on the sample construction and the number of firms within each industry see Section 2.
Source: Authors' computations based on ESEE data.

A.2 Classification of industries

Table A.1: Correspondence between ESEE industries and broader manufacturing sectors

Sectors	ESEE Industries
1. Metals and metal products	12. Basic metal products
	13. Fabricated metal products
2. Nonmetallic minerals	11. Nonmetal mineral products
3. Chemical products	9. Chemicals and pharmaceuticals
	10. Plastic and rubber products
4. Agricultural and industrial machinery	14. Machinery and equipment
5. Electrical goods	15. Computer products, electronics and optical
	16. Electric materials and accessories
6. Transport equipment	17. Vehicles and accessories
	18. Other transport equipment
7. Food, drink, and tobacco	1. Meat products
	2. Food and tobacco
	3. Beverage
8. Textile, leather, and shoes	4. Textiles and clothing
	5. Leather, fur and footwear
9. Timber and furniture	6. Timber
	19. Furniture
10. Paper and printing products	7. Paper
	8. Printing

Notes: We exclude 'Other manufacturing' (ESEE industry 20) from the analysis.

A.3 Descriptive Statistics

Table A.2: Descriptive statistics

	Robots	No Robots
Output (in logs)	9.870	8.219
	(1.666)	(1.632)
labor input (in logs)	5.506	4.325
	(1.298)	(1.177)
Material input (in logs)	9.485	7.745
	(1.766)	(1.816)
Capital stock (in logs)	8.935	6.882
	(1.872)	(2.008)
Average wage (in logs)	2.711	2.415
	(0.426)	(0.476)
R&D (in logs)	2.993	1.128
	(3.172)	(2.266)
Share of temp. workers	0.217	0.275
	(0.193)	(0.227)
Share of subcontracting	0.096	0.083
	(0.187)	(0.174)
Export share	0.268	0.132
	(0.285)	(0.238)
Investments in machinery	0.622	0.476
	(0.339)	(0.404)
Observations	7730	8850

Notes: The table shows averages (standard errors in parentheses) for key variables used in the analysis across observations with and without robots. Output, material input, and capital stock are deflated using firm-level price indices (replaced with industry-level price indices when necessary). Further details on the variable definitions are provided in Section 2.
Source: Authors' computations based on ESEE data.

A.4 Production function estimation

Table A.3: Parameters of the estimated equations

Industry	Firms	Obs.	Equation (7) σ (s.e.)	χ^2 (d.o.f)	p-val.	Equation (10) β_K (s.e.)	ν (s.e.)	χ^2 (d.o.f)	p-val.	$\eta(p_{-1}, D_{-1})$
1. Metals and metal products	340	2358	0.886	48.313	0.172	0.061	0.899	4.188	0.758	2.177
			(0.140)	(40)		(0.014)	(0.050)	(7)		
2. Nonmetallic minerals	170	1177	0.468	53.045	0.081	0.679	1.024	2.627	0.917	2.216
			(0.094)	(40)		(0.177)	(0.070)	(7)		
3. Chemical products	287	1872	0.744	55.863	0.049	0.395	0.878	6.051	0.534	2.022
			(0.094)	(40)		(0.076)	(0.046)	(7)		
4. Agricultural and industrial machinery	139	921	0.396	40.277	0.458	0.024	0.864	3.787	0.804	4.139
			(0.061)	(40)		(0.010)	(0.040)	(7)		
5. Electrical goods	165	1128	0.955	36.695	0.620	0.837	0.977	0.782	0.998	2.956
			(0.056)	(40)		(0.076)	(0.195)	(7)		
6. Transport equipment	170	1285	0.860	45.236	0.263	0.546	0.920	20.065	0.005	2.409
			(0.104)	(40)		(0.103)	(0.050)	(7)		
7. Food, drink, and tobacco	405	3040	0.767	56.000	0.048	0.209	0.964	11.389	0.123	2.153
			(0.098)	(40)		(0.048)	(0.032)	(7)		
8. Textile, leather, and shoes	315	2114	0.301	48.949	0.157	0.107	0.830	3.013	0.884	2.010
			(0.078)	(40)		(0.036)	(0.070)	(7)		
9. Timber and furniture	214	1440	0.172	54.288	0.065	0.074	0.985	4.136	0.764	2.734
			(0.104)	(40)		(0.031)	(0.033)	(7)		
10. Paper and printing products	194	1245	0.694	55.035	0.057	0.392	0.957	0.388	1.000	1.971
			(0.090)	(40)		(0.095)	(0.042)	(7)		

Notes: Hansen (1982) two-step GMM estimator.

A.5 Comparison of productivity measures

Table A.4: Hicks-neutral and labor-augmenting technological change

	Levels				Growth rates			
	ω_L		ω_H		$\Delta\omega_L$		$\Delta\omega_H$	
Industry	$rbn = 1$	$rbn = 0$	$rbn = 1$	$rbn = 0$	$rbn = 1$	$rbn = 0$	$rbn = 1$	$rbn = 0$
1. Metals and metal products	1.900	1.211	0.755	0.429	0.036	0.022	0.056	0.040
2. Nonmetallic minerals	0.504	0.373	-0.337	0.110	0.015	0.023	0.005	0.000
3. Chemical products	0.926	0.752	1.458	1.272	-0.001	0.003	0.024	0.004
4. Agricultural and industrial machinery	1.071	0.929	1.363	1.350	0.005	0.021	0.006	-0.019
5. Electrical goods	1.789	2.627	0.613	0.793	-0.191	-0.110	0.018	-0.022
6. Transport equipment	1.053	0.727	1.261	1.197	0.015	-0.076	0.005	-0.005
7. Food, drink, and tobacco	1.390	1.532	0.533	0.434	-0.020	-0.002	0.015	0.016
8. Textile, leather, and shoes	0.624	0.455	2.730	3.309	0.006	0.000	-0.015	-0.084
9. Timber and furniture	0.540	0.354	2.444	4.424	0.041	0.022	-0.224	-0.304
10. Paper and printing products	0.966	0.822	0.697	0.839	-0.006	0.029	0.007	-0.014

A.6 Productivity process (alternative specification)

Table A.5: Estimates of Multidimensional Productivity and Robots

	Total ($\omega_{T,t}$)	labor-augmenting ($\omega_{L,t}$)	Hicks-neutral ($\omega_{H,t}$)
Robots_{t-1}	0.175^{***}	0.0854^{***}	0.0758^{**}
	(0.0581)	(0.0210)	(0.0342)
$\text{Productivity}_{t-1}$	0.966^{***}	0.965^{***}	0.952^{***}
	(0.00590)	(0.00625)	(0.00651)
$\text{Productivity}^2_{t-1}$	-0.00324^{***}	-0.00141	-0.00127^{***}
	(0.000399)	(0.00134)	(0.000358)
$\text{Productivity}^3_{t-1}$	-0.0000790^{***}	-0.00364^{***}	-0.0000666^{***}
	(0.00000529)	(0.000141)	(0.00000552)
$\text{Productivity}_{t-1}\times \text{Robots}_{t-1}$	0.0163	0.0463^{***}	-0.00570
	(0.0301)	(0.0166)	(0.0377)
$\text{Productivity}^2_{t-1}\times \text{Robots}_{t-1}$	-0.0140^{***}	-0.0379^{***}	-0.00199
	(0.00349)	(0.00313)	(0.0156)
$\text{Productivity}^3_{t-1}\times \text{Robots}_{t-1}$	0.0000896	0.00289^{***}	0.0000809
	(0.000142)	(0.000170)	(0.00146)
Observations	8770	8770	8770
R-squared	0.845	0.864	0.812

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

A.7 Long-difference regression model (alternative specification)

Table A.6: Robots, Technological Change, and Labor Share in the Long Run

	Δs_L		$\Delta\omega_L$		$\Delta\omega_H$	
	(1)	(2)	(3)	(4)	(5)	(6)
Robots	-0.0103***	-0.00372	0.506***	0.406**	0.0608	0.0898**
	(0.00289)	(0.00303)	(0.165)	(0.174)	(0.0411)	(0.0436)
$s_{L,0}$	-0.0265***	-0.0346***	-0.878***	-0.741***	-0.0590	-0.0936**
	(0.00306)	(0.00330)	(0.175)	(0.189)	(0.0435)	(0.0474)
$\omega_{L,0}$	0.00000407	0.00000470	-0.0632***	-0.0615***	-0.000768	-0.000745
	(0.0000739)	(0.0000739)	(0.00422)	(0.00425)	(0.00105)	(0.00106)
$\omega_{H,0}$	0.000107	-0.000300	-0.00292	0.00396	-0.0737***	-0.0792***
	(0.000169)	(0.000190)	(0.00966)	(0.0109)	(0.00241)	(0.00274)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Selection controls	No	Yes	No	Yes	No	Yes
Observations	2399	2376	2399	2376	2399	2376
R-squared	0.056	0.080	0.160	0.163	0.338	0.345

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Cross-section, number of observations is the number of firms.

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