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Robots & the Rise of European Superstar Firms

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Abstract

We estimate the impact of a recent digital automation technology - industrial robotics - on the distribution of productivity and markups within industries. Our empirical analysis combines data on the industry-level stock of industrial robots with firms' balance sheet data for six European countries from 2004 to 2013. We find that robots dis-proportionally raise productivity in those firms that are already most productive to begin with. Those firms are able to increase their markups, while markups tend to decline for less profitable firms within the same industry, country and year. We also show that industrial robots contribute to the falling aggregate labour income share through a rising concentration of industry sales. In short, our paper suggests that robots boost the emergence of superstar firms within European manufacturing, and thereby shifts the functional income distribution away from wages and towards profits.

JEL Classification: D4, L11, O33.

Keywords: Automation, industrial robots, productivity, markups, labour share, superstar firms.

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1 Introduction

"A small group of giant companies – some old, some new – are once again dominating the global economy [...]" . This assessment by The Economist (2016) from its piece *The rise of the superstars*, referred mostly to American internet giants such as *Google* or *Apple*. But also apart from those well publicized cases, recent research suggests that the previous decades were more broadly characterized by a reallocation of production and market shares towards highly productive and profitable firms – with notable implications for competition, market power, and the income distribution.

In the United States (US), market concentration has increased in more than 75% of all industries during the last 20 years according to Grullon et al. (forthcoming), while average markups have risen mainly because highly profitable firms were able to grasp additional market shares (De Loecker and Eeckhout, 2017, 2018). This elevated market power, in turn, has aggregate implications as it seems to be tightly linked to the falling labor share of income (Autor et al., 2017a,b; Kehrig and Vincent, 2018). Those trends are particularly strong in the US, but they have been uncovered, though somewhat muted, also in other countries. Andrews et al. (2016) find that global frontier firms – the top 5% most productive firms within an industry and year – have significantly gained market share relative to laggards across all OECD members, and Calligaris et al. (2018) document an average markup increase of 5% between 2001 and 2014 for firms in 26 countries worldwide.

An important and yet unresolved question is: what are the underlying drivers of this superstar firm pattern? Explanations for the observed increase in productivity dispersion and the concentration of market power include limited antitrust enforcement and increasing regulation (e.g., Gutiérrez and Philippon, 2017, 2018), as well as increased import competition as a result of globalization (e.g., Autor et al., 2017b). But one key explanation, emphasized by The Economist (2016) and many others, seems to be the role of *technology*. If newly emerging technological possibilities accrue primarily to (or were developed by) the most productive firms within an industry, they get even more productive, gain larger market shares, and charge higher markups. Empirical evidence on the drivers of this superstar phenomenon, in particular on the role of technology, is however limited.

In this paper, we examine the role of one particular new digital technology, industrial robots, in shaping the distribution of firm-level productivity and markups within industries. At first we document that the superior (productivity and markup) growth performance of already productive and profitable firms is also a feature of some (though not all) European manufacturing branches. We then investigate which industries tend to exhibit this pattern, and find that it is considerably stronger in more robotized industries: Robots drive the emergence of superstar firms.

We exploit data for six European countries (France, Germany, Italy, Spain, Finland, and Sweden) from 2004 to 2013, and our results indicate that an increase in the stock of industrial robots dis-proportionally benefits the firms that already exhibited the highest levels of productivity and markups to begin with. More specifically, we find a rise in TFP for the top 20% of firms with the highest initial productivity, but an insignificant effect on the other firms in an industry. The impact on markups also displays considerable heterogeneity: while robotization negatively affects the markups of firms with initially low and medium markups, it allows the top 10% of firms to increase their markups even further. In addition, we provide evidence that industrial robots contribute to the falling labor share through an increased concentration of industry sales in low labor share firms.

Related literature. The rise of superstar firms and its economic impact has been analyzed by Autor et al. (2017a,b) in the context of the falling labor income share observed in recent decades. In their stylized model, superstar firms are highly productive firms, which are characterized by high profits and a low share of labor in firm value-added and sales. If a change in environment (for instance the introduction of a new technology) mostly benefits these firms, and if they subsequently gain a greater market share, then the industry's aggregate labor share decreases due to the reallocation of output towards these low labor share firms.[1] Apart from the falling labor income share, the superstar firm hypothesis is related to further secular economic trends that have been observed over the last decades. First, while global productivity growth is slowing down (e.g., Syverson, 2017), productivity is rising for a set of firms at the productivity frontier leading to productivity divergence (e.g.: Andrews et al., 2016; Haldane, 2017). More specifically, defining frontier firms as the top 5% most productive firms within an industry and year for 24 OECD countries, Andrews et al. (2016) document an increasing productivity gap between frontier and laggard firms between 1997 and 2014, with annual growth rates of around 3% for the former and of around 0.5% for the latter. This evidence is consistent with Bahar (2018) who estimates a U-shape relationship between productivity growth and initial levels within country-industry cells.

Furthermore, markups are rising in various countries and industries, and the increase in average markups is driven by firms at the top of the markup distribution. De Loecker and Eeckhout (2017) document the divergence of markups using data on publicly traded firms in the US from 1980 onwards, and show that it mainly stems from a change in markups *within* rather than *between* industries.[2] For European countries, the divergence of markups is less pronounced. According to Weche and Wambach (2018), also the median markup has increased in recent years, in contrast to the US where the increase in average markups is entirely driven by high markup firms. Moreover, while

[1] Kehrig and Vincent (2018) propose a similar mechanism confirming the reallocation of production towards so-called *hyper-productive* establishments in US industries. Gutiérrez and Philippon (2019), in contrast, show that superstar firms in the United States have not become larger and their contribution to overall productivity growth through reallocation has only increased modestly over the past 60 years.

[2] Hall (2018) also documents rising markups in the US economy by using data at the sectoral level, but the increase in less pronounced than in the work of De Loecker and Eeckhout (2017).

focusing on the development of markups during and after the 2008 financial crisis, the authors show that average markups have dropped during the crisis and not fully recovered in several european countries, whereas in the US average markups already exceeded pre-crisis levels in 2011.

So far, direct evidence on the drivers behind this emergence of superstar firms has been limited, especially when it comes to the impact of new technologies. Our paper goes a first step in that direction. Thereby we extend a recently growing literature which analyzes the impact of new technologies on various industry-level measures such as market concentration or average firm sizes.[3] Yet, these studies mainly exploit data on general ICT or related technologies and largely focus on industry-level outcome variables. A small number of papers have instead used micro-level data on technology adoption, however, this evidence is either based on correlations (Dinlersoz and Wolf, 2018), or limited to a specific firm outcome like sales (Lashkari and Bauer, 2018).

Bessen (2017) finds that the use of proprietary information technology (IT) systems increases industry concentration, measured by the shares of sales to the top firms. Moreover, the use of such IT systems is associated with relatively higher labor productivity for the top four firms within an industry. Autor et al. (2017b) explore two measures of technical change – patent-intensity and TFP –, and identify a positive correlation with the growth in industry concentration. In addition, pointing to a potential slowdown in technological diffusion, they show that industries with a drop in the speed of patent citations experience a higher rise in concentration rates. In a recent study, Dinlersoz and Wolf (2018) investigate the link between technology adoption, superstar firms, and the labor share, by exploiting plant-level information on technology use and investment from the U.S. Census Bureau's 1991 Survey of Manufacturing Technology. The cross-sectional data shows that more productive and larger plants tend to be more automated. In addition, more technologically advanced plants have a lower production labor share and experience larger declines in that share on a five-to-ten year horizon. While the micro data allows detailed insights into the type of firms that adopt new technologies, the direction of effects remains unclear. In another study, Lashkari and Bauer (2018) examine the relationship between firm size and IT intensity using micro data on software and hardware investment in french firms. Consistent with a non-homothetic IT demand, they estimate a positive and significant elasticity of IT intensity with respect to exogenous variations in firm size. Hence, a fall in the price of IT dis-proportionally benefits large firms, which may in turn explain the reallocation effect towards superstar firms.

The present work is more generally related to a large literature studying the determinants of productivity dispersion within narrowly defined industries, as surveyed in Syverson (2011). Different explanations have been proposed, both on the supply-side like innovation (e.g., Foster et al., 2018),

[3]See, for instance, Bessen (2017), Autor et al. (2017b), Dinlersoz and Wolf (2018), and Lashkari and Bauer (2018).

management practices (e.g., Bloom and Van Reenen, 2010), or resource misallocation across firms (e.g.: Hsieh and Klenow, 2009; Gopinath et al., 2017), as well as on the demand-side like product substitutability (Syverson, 2004). Regarding the effect of technology and innovation on productivity, an extensive literature focuses on ICT (e.g.: Oliner and Sichel, 2000; Jorgenson, 2001; Bartel et al., 2007; Inklaar et al., 2008), identifying important contributions both in the short and in the long run (Brynjolfsson and Hitt, 2003), which are mainly driven by IT-intensive sectors (Stiroh, 2002).[4] A newer wave of automation is investigated by Graetz and Michaels (2018), who draw on the industrial robot data from the IFR, and find a positive impact on labor productivity and TFP. The same data set has also been used by Acemoglu and Restrepo (2017) and Dauth et al. (2018) to examine the labor market effects of robots in the US and Germany, respectively.

Our work also speaks to the literature on the determinants of the downward trend in the aggregate labor share of income which can be observed in many countries over the last decades. The proposed explanations include, among other things, the decline in the price of capital relative to labor associated with technological advancement (e.g.: Karabarbounis and Neiman, 2014; Dao et al., 2017; Autor and Salomons, 2018), trade and international outsourcing (e.g.: Elsby et al., 2013; Dao et al., 2017; Guschanski and Onaran, 2017), and falling bargaining power of labor (e.g.: Bental and Demougin, 2010; Guschanski and Onaran, 2017). Most of this literature relies on aggregate industry information and therefore neglects heterogeneity between firms. One exception is Adrjan (2018) who exploits data on UK firms and finds that those with a higher capital intensity allocate a smaller share of their value added to workers, which is in line with a declining relative price of capital. In addition, firms with greater market power (measured by the sales portion) display a lower labor income share, consistent with the reallocation mechanism proposed in Autor et al. (2017a,b).

Moreover, recent works by Autor et al. (2017a,b) and Kehrig and Vincent (2018) suggest a new explanation for the fall in the aggregate labor share observed in recent decades: the reallocation of production towards highly productive firms with a low labor share. We contribute to this literature by analyzing the impact of robotization on the aggregate labor share, calculated either based on unweighted or on sales-weighted averages of firm-level labor costs over sales. Hence, we directly investigate the role of industrial robots in reducing the aggregate labor share through two different channels: a fall within firms, or a reallocation of sales between heterogeneous firms.

The rest of this paper is organized as follows. Section 2 introduces the data sources and Section 3 describes the empirical strategy. In Section 4, we present our main results for the impact of robots on productivity and markup distributions including various robustness checks. Section 5 studies the effects on industry concentration and the labor share. Section 6 concludes.

[4] Note that Acemoglu et al. (2014) find little evidence that productivity was growing faster in IT-intensive sectors after the late 1990s using US manufacturing data.

2 Data

2.1 Robot data

Our main data set consists of the stock of industrial robots by country, industry, and year, and is released by the International Federation of Robotics (2016). [5] The global robot market is growing strongly: in 2017, robot sales increased by 21% to a new peak at US$16 billion, not even taking into account the cost of software, peripherals, and systems engineering (International Federation of Robotics, 2018).

The IFR records the installations of industrial robots on the basis of yearly surveys of nearly all industrial robot suppliers worldwide. A *robot* is defined as an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (International Federation of Robotics, 2016, p. 25), according to the definition of the International Organization for Standardization (ISO 8373). Examples of industrial robot applications include welding, painting, palletizing, packaging, and handling materials. As explained by the International Federation of Robotics (2016), the definition excludes so-called *dedicated* robots (as opposed to *multipurpose* robots) which cannot be adapted to a different application, such as automated storage and retrieval systems in warehouses.

We use annual data on the stock of industrial robots for six European countries, namely France, Germany, Italy, Spain, Finland, and Sweden, for the period from 2004 to 2013.[6] The national information is broken down by industrial branches according to the International Standard Industrial Classification of All Economic Activities (ISIC) Revision 4. We focus on the manufacturing sector, and are able to differentiate 14 industries.[7] Figure 1 depicts the change in the number of robots per thousand workers between 2004 and 2013. While the robot density varies considerably by country and industry, the strongest increase is generally observed in the manufacture of pharmaceuticals and cosmetics, of rubber and plastic products, and of motor vehicles. In these industries, up to 40 additional robots per thousand workers were installed in the period from 2004 to 2013. Industries with no change or even a decline in robot usage are for example textiles, other chemical products, other non-metallic mineral products, and electronics.

[5] This data set has already been used by Graetz and Michaels (2018), Acemoglu and Restrepo (2017), and Dauth et al. (2018), primarily to evaluate the labor market effects of robots.

[6] The choice of countries is driven by the availability of comprehensive firm-level balance sheet information from the Amadeus database.

[7] We do not use the IFR industries *all other manufacturing*, *all other non-manufacturing*, *unspecified*, *unspecified metal*, and *unspecified chemical products*, as these robot counts cannot be clearly assigned to one of the 14 industries.

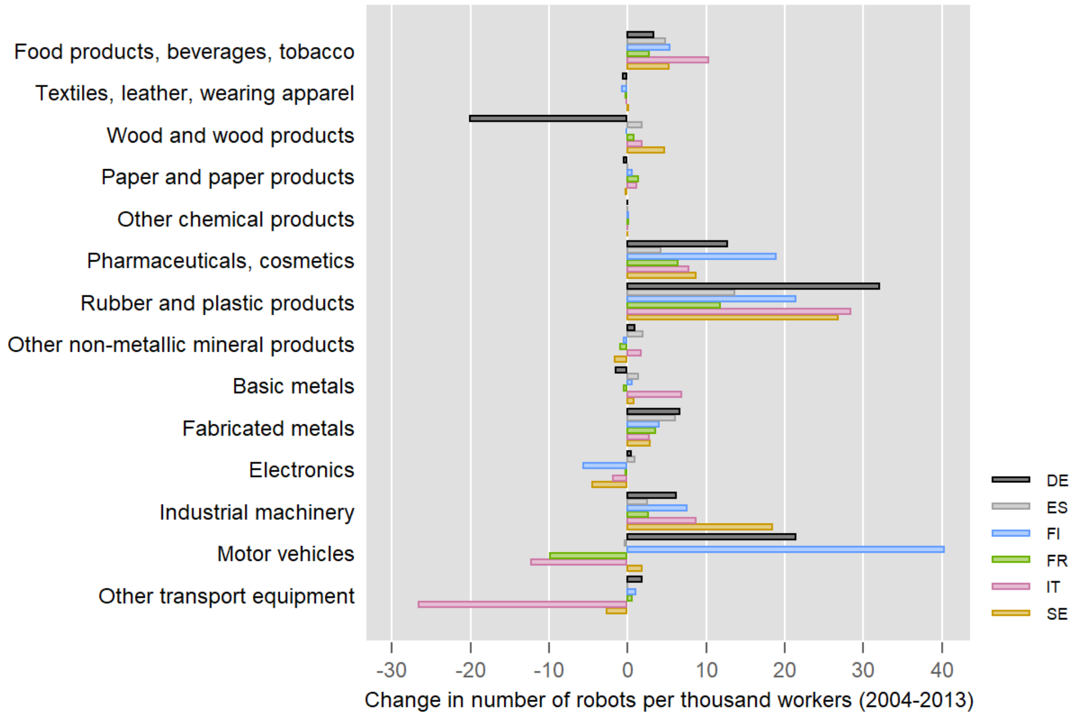

Figure 1: Industry-level distribution of robots.

Note. The figure displays the change in the number of robots per thousand workers by ISIC Rev. 4 industries between 2004 and 2013 in Germany, Spain, Finland, France, Italy, and Sweden. Employment is measured as the number of employees in 2004. Sources: IFR, OECD Stan, own calculations.

2.2 Firm-level data

The second major data source is the Amadeus database which contains standardized annual accounts of public and private European firms.[8] It is collected by Bureau van Dijk on the basis of company filings and reports, and includes detailed information on firms' balance sheet and profit and loss accounts. The comparability of data across countries and the classification of firms into 2-digit NACE[9] industries make the data well suited for cross-country, cross-industry analyses. One limitation of the Amadeus database is the incomplete identification of entry and exit of firms. For instance, when a firm enters the sample in a given year, it is not clear whether this is also the year where the firm has entered the market. This is potentially problematic, because there are two channels how robots may affect the distribution of firm performance within industries: heterogeneous

[8]The Amadeus database has been used in many empirical studies in international economics as well as in the productivity and industrial organization literature (see, e.g.: Helpman et al., 2004; Konings and Vandenbussche, 2005; Stiebale, 2016; Gopinath et al., 2017).

[9]NACE describes the statistical classification of economic activites in the European Communities, derived from the French title *Nomenclature générale des Activités économiques dans les Communautés Européennes*.

responses of incumbent firms, or firms entering and/or exiting the market.[10] Since the information on entry and exit is not reliable, we focus on the first channel. In the empirical application, as will be explained in more detail in Section 3.2, we use incumbent firms which are present both in the first and in the last year of any five-year period between 2004 and 2013.

The Amadeus data set is primarily used for the production function estimation, with the aim of estimating firm-level TFP and markups. In doing so, output is measured as sales, labor input as the number of employees, material input as material costs, and the capital stock is approximated by tangible fixed assets. In addition, information on labor costs and capital depreciation are exploited to calculate average wages, the labor share, and capital investments.[11] Furthermore, in order to control for industry-level foreign direct investment (FDI) in the regression analysis, we compute the market share of foreign-owned firms in each 2-digit industry.[12]

The financial variables are adjusted using industry-level deflators for production, gross fixed capital formation, and intermediate inputs from the OECD STructural ANalysis (STAN) database.[13] Moreover, we drop a small number of firms where only consolidated balance sheet information is available, i.e., the combined financial statements of a parent company and all its subsidiaries. In addition, to deal with extreme outliers, the lower and the upper 0.5% quantile of each variable is set to missing. Summary statistics for the firm-level variables are reported in Table 1.

Table 1: Summary statistics of firm-level variables.

Variable	Definition	Mean	Std. dev.	Obs.
Sales	Total operating revenues	12,983.56	38,942.83	1,034,632
Labor	Total number of employees	53.70	118.12	914,900
Materials	Material costs	7,456.90	23,286.33	851,258
Capital stock	Tangible fixed assets	2,620.64	7,897.14	966,819
Average wages	Costs of employees / Labor	37.19	14.12	783,600
Labor share	Costs of employees / Sales	0.24	0.14	913,402
Capital investment	Investment in tangible fixed assets	408.89	1,928.41	814,537

Note. The variables are measured annually. The financial variables are given in thousand euros. The data includes firms in the manufacturing sector (NACE Rev. 2, 2-digit industry codes 10-30) in France, Germany, Italy, Spain, Finland, and Sweden between 1997 and 2015. Sources: Amadeus, own calculations.

[10] See Bahar (2018) who also discusses these two channels in the context of a change in the within-industry productivity dispersion between two periods.

[11] Capital investment is calculated by applying the perpetual inventory method as for example in Collard-Wexler and De Loecker (2016), i.e., $I_{it} = K_{it+1} - K_{it} + \delta K_{it}$, with I describing the capital investment, K the capital stock, and δ the depreciation factor, for firm i at time t.

[12] A firm is defined as foreign-owned if the stake controlled by foreign shareholders is greater than 50%. To calculate their market share, firms are weighted by sales.

[13] For Spain, the industry deflators for production and intermediate inputs are unfortunately not available. In this case, we use the industry-level total output price index from the Eurostat Structural Business Statistics (SBS) database to deflate the relevant variables.

2.3 Other industry data

To consider earlier waves of automation and other measures related to innovation and technology, we use data from the EU KLEMS September 2017 release (Jäger, 2017). The database includes information on gross fixed capital formation (i.e., investments) of computing and communications equipment – also known as ICT –, of computer software and databases, and of research and development (R&D) by industry and country.[14] In order to make the variables comparable across countries, we follow Graetz and Michaels (2018) and convert the nominal values to 2010 US$ by using the annual nominal exchange rates from the Penn World Table, Version 8.0 (Feenstra et al., 2015). We further exploit data on industry-level wages (labor compensation in 2010 US$ divided by total hours worked by persons engaged), and on the capital-to-labor ratio (capital over labor compensation).

To account for potential confounding effects of international trade in the regression analysis, we construct imports and exports at the industry level using data from the United Nations International Trade Statistics Database (Comtrade). The trade data is provided according to the Standard International Trade Classification (SITC) Revision 3, and is converted to ISIC Revision 4 industries using official cross-walks by the World Bank and Eurostat.[15] The variables are measured in 2010 US$ by deflating current US$ with the consumer price index of the World Bank.[16] Finally, the robot density – the number of robots per thousand workers – is calculated by relying on employment data from the OECD STAN database.[17]

3 Econometric strategy

The empirical strategy of this paper consists of two steps. We start with the production function estimation to measure firm productivity and markups. In the second step we then use those variables to evaluate the effects of robots on (the distribution of) firm-level productivity and markups within industries.

[14] As both the IFR and the EU KLEMS data are reported according to the ISIC Rev. 4 industry classification, no industry mapping is necessary.

[15] The conversion of the SITC Rev. 3 to the ISIC Rev. 4 industry classification includes three cross-walks, namely SITC Rev. 3 to NACE Rev. 1, NACE Rev. 1 to NACE Rev. 1.1, and NACE Rev. 1.1 to NACE Rev. 2. Note that NACE Rev. 2 is the same as ISIC Rev. 4 for 2-digit industries which is sufficient for our purposes. See Appendix A.1 for more details.

[16] https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=US

[17] For Sweden, the employment data is not available separately for the ISIC Rev. 4 industries 20 and 21. In this case, employment data from Eurostat SBS is used to calculate the respective shares and to distribute the number of employees accordingly.

3.1 Estimating productivity and markups

Consider a production function for firm i at time t:

$$Q_{it} = F(K_{it}, L_{it}, M_{it})\Omega_{it}, \tag{1}$$

where Q_{it} denotes output, K_{it} denotes the capital stock, L_{it} and M_{it} are labor and material inputs respectively, and Ω_{it} denotes total factor productivity (TFP).

In the empirical literature, two widely used functional forms are the Cobb-Douglas and the translog production functions. On the one hand, the Cobb-Douglas production function is convenient because of the relatively few parameters to estimate and the straightforward interpretation of production coefficients. On the other hand, the translog production function is more flexible and less restrictive with regard to, for example, the output elasticities and the elasticity of substitution between input factors. However, it requires the estimation of a high number of parameters, which potentially implies collinearity problems. In our application, the Cobb-Douglas functional form has one distinct advantage compared to the translog case: Since output cannot be measured in physical quantities but is proxied by deflated sales (based on an industry-level output deflator), the production function coefficients may be biased when the firms operate in an imperfectly competitive environment (Klette and Griliches, 1996).

The Cobb-Douglas model assumes that all firms have the same output elasticities, hence this potential output price bias is at least the same for all firms.[18] In the main analysis of the paper, we therefore assume a Cobb-Douglas production function, and we later check the robustness of results with regard to a translog functional form.

When assuming the functional form $F(.)$ in Equation (1) to be Cobb-Douglas and taking logarithms on both sides of the equation, we get the following regression equation:

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it}, \tag{2}$$

where q_{it}, k_{it}, l_{it}, m_{it}, and ω_{it} are the logarithmic output, inputs and TFP respectively, and ϵ_{it} is an additive error term. If the TFP is observed by the firm (for instance, management skills or employed technology), firms' input decisions may depend on ω_{it}. To deal with this potential endogeneity problem, we follow the methodology by Ackerberg et al. (2015). They employ a semi-parametric approach building on Olley and Pakes (1996) and Levinsohn and Petrin (2003) who proxy unobserved time-varying productivity by investment respectively intermediate inputs under

[18] Note that in the empirical application, we estimate the production function separately by industry, implying that the output price bias is the same for all firms in an industry when assuming a Cobb-Douglas production function.

certain identifying assumptions.

Productivity is assumed to evolve according to a (first-order) Markov process, where actual productivity can be decomposed into expected productivity given the information set of firm i and a random shock ξ_{it}. Since we are interested in the effect of robots on firm productivity later on, we allow the change in the industry-level log robot stock $\triangle robots_{jt-1}$ to impact future productivity:

$$\omega_{it} = g(\omega_{it-1}, \triangle robots_{jt-1}) + \xi_{it}.^{19} \tag{3}$$

The timing of input choices is as follows. Capital and labor are dynamic inputs that are costly to adjust and therefore partly fixed in the short-run.[20] By contrast, materials are non-dynamic and freely adjustable. A firm decides upon its material input in period t after observing its productivity, capital and labor. Additionally, we let material demand depend on the log change in robots and firm-level log wages, as well as on country and time (by including country and year dummies $\boldsymbol{C}_c$ and $\boldsymbol{Y}_t$ respectively):

$$m_{it} = f(\omega_{it}, k_{it}, l_{it}, \Delta robots_{jt-1}, wage_{it}, \boldsymbol{C}_c, \boldsymbol{Y}_t).^{21} \tag{4}$$

Assuming that the firm-level material choice is a strictly increasing function of unobserved productivity, f can be inverted such that ω is a function of observables:

$$\omega_{it} = f^{-1}(m_{it}, k_{it}, l_{it}, \Delta robots_{jt-1}, wage_{it}, \boldsymbol{C}_c, \boldsymbol{Y}_t). \tag{5}$$

The production function in Equation (2) can thus be rewritten as

$$\begin{aligned} q_{it} &= \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + f^{-1}(\cdot) + \epsilon_{it} \\ &= \Phi(k_{it}, l_{it}, m_{it}, \Delta robots_{jt-1}, wage_{it}, \boldsymbol{C}_c, \boldsymbol{Y}_t) + \epsilon_{it}. \end{aligned} \tag{6}$$

The estimation procedure is performed separately for 2-digit NACE Revision 2 industries. In the first stage, Φ_{it} is approximated by a cubic polynomial and Equation (6) is estimated by ordinary least squares (OLS).[22] To account for measurement error in the capital stock, k_{it} is instrumented

[19] The idea to incorporate the policy variables of interest in the productivity process follows De Loecker (2013) who includes a firm's exporting experience, and is also applied by for example Brandt et al. (2017) and Doraszelski and Jaumandreu (2018).

[20] In contrast to Olley and Pakes (1996) and Levinsohn and Petrin (2003), Ackerberg et al. (2015) allow labor to have dynamic implications. As the labor markets in our sample of European countries are rather rigid, this seems to be a reasonable assumption.

[21] We follow De Loecker and Scott (2016) and exploit firm-level wages (i.e., variation in firm-specific input prices) in order to deal with the identification problem in the production function estimation when using intermediate inputs as a proxy for productivity (Gandhi et al., 2016).

[22] More specifically, Φ_{it} is approximated by a linear combination of its arguments, with a cubic polynomial in

with lagged investment (Collard-Wexler and De Loecker, 2016). In this stage the production input coefficients are not identified. However, we obtain an estimate of the output net of ϵ_{it} which is utilized to express productivity as

$$\omega_{it} = \hat{\Phi}_{it} - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it}. \tag{7}$$

In the second stage, we use the law of motion in Equation (3) and the assumptions on the timing of inputs to specify the moment conditions:

$$E\left[\xi_{it}(\beta_k, \beta_l, \beta_m)\begin{pmatrix} i_{it-1} \\ l_{it} \\ m_{it-1} \end{pmatrix}\right] = 0, \tag{8}$$

and identify the production function parameters by applying the generalized method of moments (GMM).[23] In doing so, g is approximated by a 3-order polynomial in its arguments. TFP can then be calculated with the formula in Equation (7).

We follow De Loecker and Warzynski (2012) to measure a firm's markup. Assuming cost-minimizing firms, the markup can be derived as

$$\mu_{it} = \frac{\beta_m}{\alpha_{it}^m}, \tag{9}$$

where β_m denotes the output elasticity of materials as in Equation (2), and α_{it}^m is the share of material expenditures in total sales.[24] The markup is therefore positive if the output elasticity of a variable factor of production is greater than its sales share. We compute markups using the estimated output elasticity of materials and the share of material costs in total sales, which is directly observed in the data. Like De Loecker and Warzynski (2012), we divide total sales by the predicted error term obtained in the first stage of the production function estimation $exp(\hat{\epsilon_{it}})$ to eliminate variation in the sales share that is not related to factors affecting input demand.

3.2 Evaluating the effects of robots

Within the context of the production function estimation, current productivity is assumed to be a function of lagged productivity and the lagged change in robots (see Equation 3). We approximate

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capital, labor, materials, and the log change in robots.

[23] Note, as already mentioned above, we use lagged investment to instrument for the current capital stock (Collard-Wexler and De Loecker, 2016).

[24] Note that we use materials as the variable factor of production, as labor is assumed to be a dynamic input characterized by adjustment costs.

this function by a cubic polynomial in its arguments, thus allowing the effect of robots to depend on the level of firm productivity.

The baseline regression equation to evaluate the impact of robots can be derived from the linear version of Equation (3), by repeatedly inserting the expression for productivity and bringing lagged productivity to the left-hand side of the equation. The change in productivity between period t and $t-s$ is therefore a function of baseline productivity in period $t-s$ and the (lagged) s period change in robots:

$$\begin{aligned} \omega_{it} &= \alpha_0 + \alpha_1 \omega_{it-1} + \beta_1 (robots_{jt-1} - robots_{jt-2}) + \xi_{it} \\ \Leftrightarrow \triangle_s \omega_{it} &= \alpha_0 + (\alpha_1 - 1)\omega_{it-s} + \beta_1 \triangle_s robots_{jt-1} + \triangle_s \xi_{it}. \end{aligned} \tag{10}$$

Consistent with Equation (10), the impact of robots is analyzed using the following baseline specification:

$$\begin{aligned} \triangle_s y_{ijct} = \gamma_0 &+ \gamma_1 y_{ijct-s} + \delta \triangle_s robots_{jct-1} \\ &+ \boldsymbol{\theta} \triangle_s \mathbf{Z}_{jct-1} + \boldsymbol{\zeta} \mathbf{W}_{jct-s} + \boldsymbol{C}_c + \boldsymbol{Y}_t + \triangle_s \nu_{ijct}, \end{aligned} \tag{11}$$

where $\triangle_s y_{ijct} = y_{ijct} - y_{ijct-s}$ denotes the s period change in the outcome of interest for firm i in industry j in country c at time t (for instance, log TFP or log markups).

$\triangle_s \mathbf{Z}_{jct-1}$ is a vector controlling for concurrent changes at the industry level that may bias the effects of robots. It includes other technologies and measures for innovation, namely the log changes in ICT, computer software and databases, and R&D, respectively. In addition, we take into account globalization with the log changes in imports and exports and the change in the share of inward FDI, and further control for the change in the capital-to-labor ratio. Initial industry controls $\mathbf{W}_{jct-s}$, that are the baseline capital-to-labor ratio and log wages, are also included as control variables.[25] Moreover, country dummies $\boldsymbol{C}_c$ and year dummies $\boldsymbol{Y}_t$ allow for country- and time-specific trends. We use overlapping differences – in the main specification five-year differences – and cluster standard errors at the country-industry pair level (Bloom et al., 2016). The regressions are estimated by OLS, while in Section 4.3 we also experiment with instrumental variables (IV) estimators.

In line with the productivity process assumed within the context of the production function estimation, we allow the impact of robots to depend on firm-level TFP (or another outcome of interest, for instance markups). Heterogeneous effects of robots are calculated by interacting the change in robots with dummy variables for different percentiles of the lagged outcome of interest, in

[25] The choice of control variables is inspired by Graetz and Michaels (2018).

the following equation exemplified on the basis of quintiles:

$$\begin{aligned}\triangle_s y_{ijct} = \delta_1(\triangle_s robots_{jct-1} \times Quin1_{ijct-s}) \\ + \cdots + \delta_5(\triangle_s robots_{jct-1} \times Quin5_{ijct-s}) + \cdots + \triangle_s \nu_{ijct},\end{aligned} \tag{12}$$

where, for example, $Quin1_{ijct-s}$ is equal to one if the lagged outcome of interest y_{ijct-s} for firm i is smaller or equal than the 20th percentile of that outcome considering all firms in the same country, industry, and year, and zero otherwise.[26] The regression equation additionally contains the dummy variables $Quin1_{ijct-s}$ to $Quin5_{ijct-s}$ themselves and the control variables as defined in Equation (11).[27] This specification allows me to evaluate the distributional effects of robots by analyzing how a change in the robot stock affects the different parts of the distribution of firm-level outcomes.

4 Empirical results

4.1 Production function estimation

In this subsection, we present the results of the production function estimation. The focus is on firm-level TFP and markups, the outcome variables for the main analysis of the paper.

The production function estimation is performed separately for 2-digit NACE Revision 2 manufacturing industries. Some industries are pooled, so that the industry aggregation matches the robot data.[28] Appendix Table A.1 presents the estimated production function coefficients for labor, materials and capital, with returns to scale ranging between 0.96 and 1.02. When estimating the production functions and throughout the analysis of the paper, the log robot stock is calculated as $ln(Robots + 1)$ to take account of zeros in the data, especially in the first years of the sample period. As we proceeded for the firm-level variables from the Amadeus database to deal with extreme outliers, we delete the lower and upper 0.5% quantile of estimated markups and TFP.

Figure 2 depicts the evolution of average firm-level TFP from 2004 to 2013 by ISIC Rev. 4 industries, where the average TFP is weighted by firm sales. For each industry and year, we calculate the average log change in TFP relative to 2004, so the changes can approximately be interpreted in percentage terms.[29] We generally observe a rise in productivity until the beginning of the financial crisis and a sharp decrease afterwards, which is only partly recovered until 2013. Out of 14

[26] The aggregation level of industries in these country-industry-year cells is the same as for the robots variable.

[27] Note that Equation (12) does not include the lagged outcome of interest y_{ijct-s} when controlling for the dummy variables $Quin1_{ijct-s}$ to $Quin5_{ijct-s}$.

[28] Note that, at the 2-digit level, the NACE Rev. 2 industry classification is equivalent to the ISIC Rev. 4, which is the industry classification of the robot data.

[29] The sample in Figure 2 includes firms which are present in the data for at least five years. This is done because the Amadeus database cannot clearly identify the entry and exit of firms, as mentioned in Section 2.2.

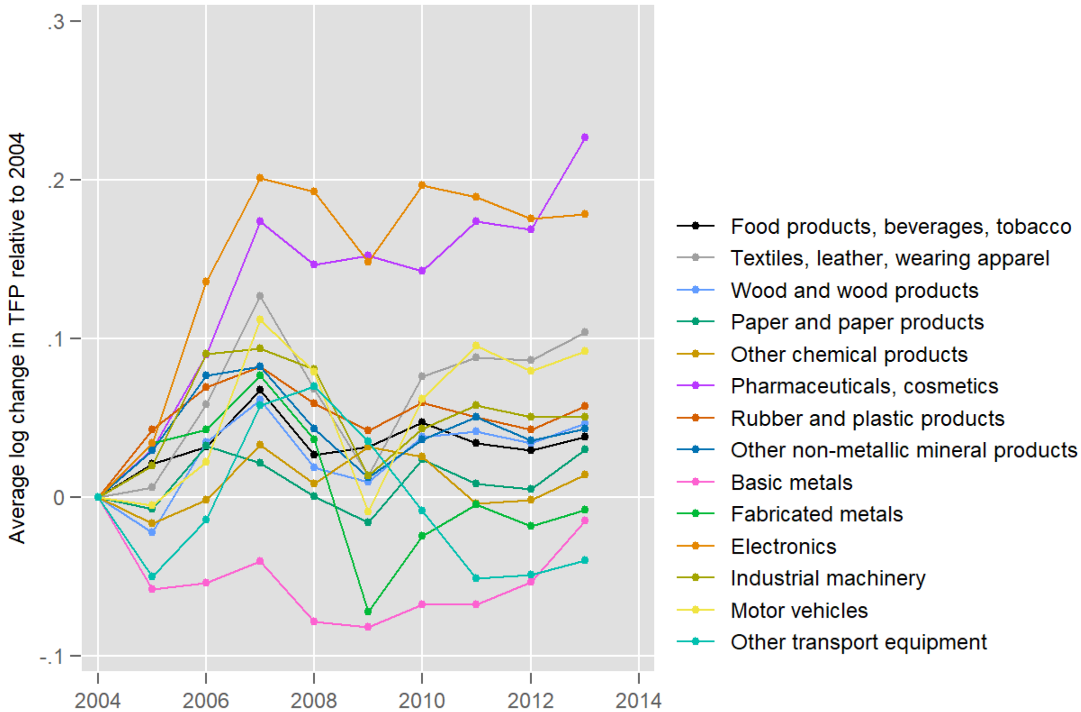


Figure 2: Industry-level evolution of TFP.

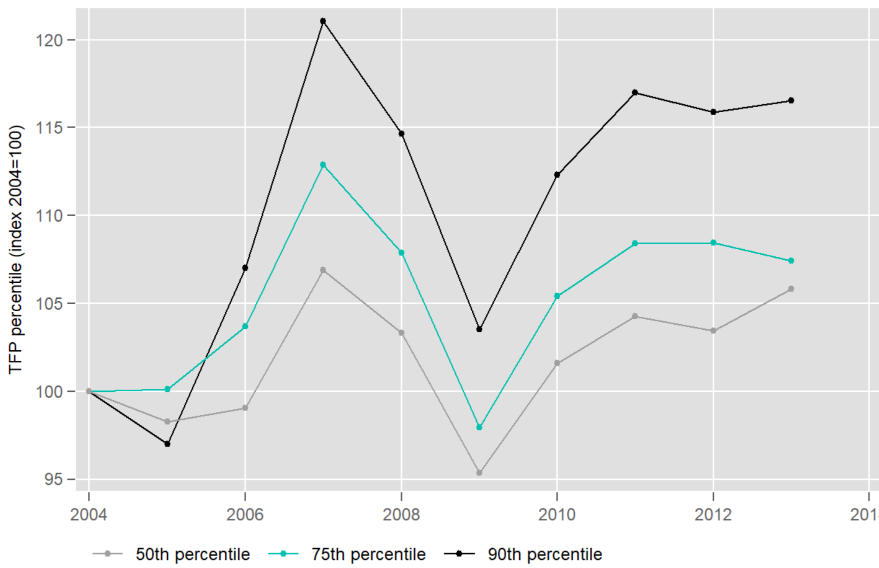
Note. The figure displays the evolution of average firm-level TFP from 2004 to 2013 by ISIC Rev. 4 industries, where the average TFP is weighted by firm sales. For each industry and year, we calculate the average log change in TFP relative to 2004. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, own calculations.

manufacturing industries, eight industries are characterized by higher average productivity in 2013 compared to 2004.

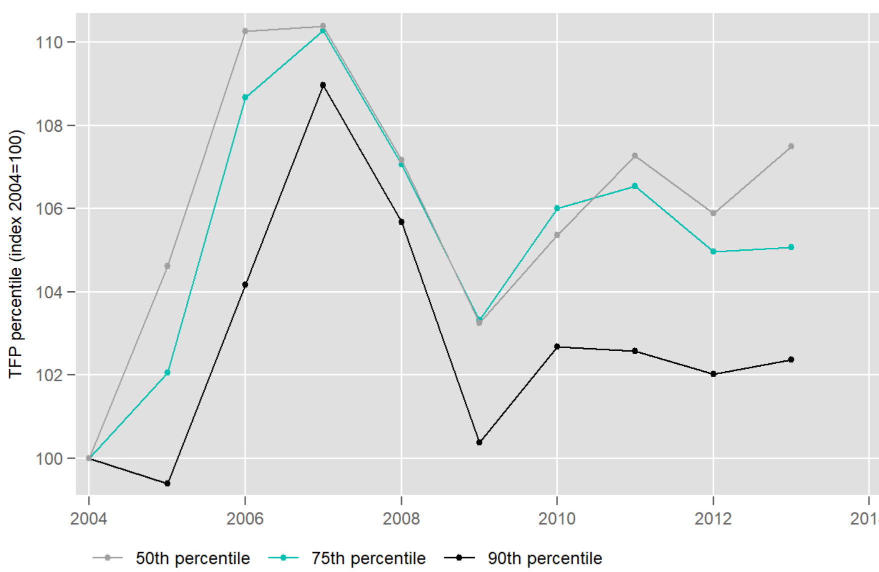
The industry with the highest average productivity increase in the observation period is the manufacture of pharmaceuticals and cosmetics (roughly 23%), followed by electronics, textiles, and motor vehicles. It is important to keep in mind that we measure revenue-based instead of physical productivity due to the lack of firm-level data on physical quantities. We account for price effects by using an industry-level output deflator. Nevertheless, the estimated productivity measure might reflect, apart from technical efficiency, heterogeneity across firms with regard to, for example, demand shifts or market power.[30]

These average industry-level evolutions of TFP are not necessary representative for performance of the most productive firms at the technological frontier within the industry. And indeed, Figure 3 illustrates the upper half of the TFP distribution for two exemplary manufacturing industries, which are picked because those two cases are also characterized by vastly different degrees of robotization.

[30] See, for instance, Forlani et al. (2016).



(a) Motor vehicles



(b) Other non-metallic mineral products

Figure 3: Evolution of TFP percentiles.

Note. The figure displays the evolution of different percentiles of the TFP distribution from 2004 to 2013, exemplarily for two manufacturing industries which are characterized by a different degree of robotization: motor vehicles (high increase in the robot density, Panel a) and other non-metallic mineral products (low increase in the robot density, Panel b). The percentiles are calculated using sales weighted firm-level TFP. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, own calculations.

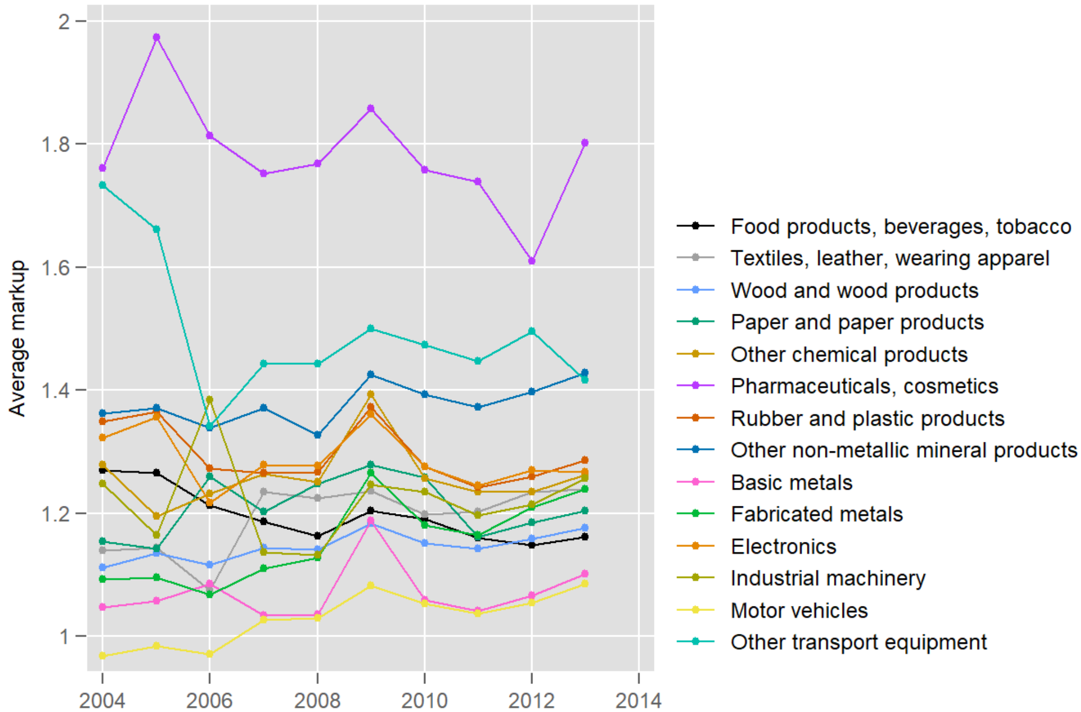


Figure 4: Industry-level evolution of markups.

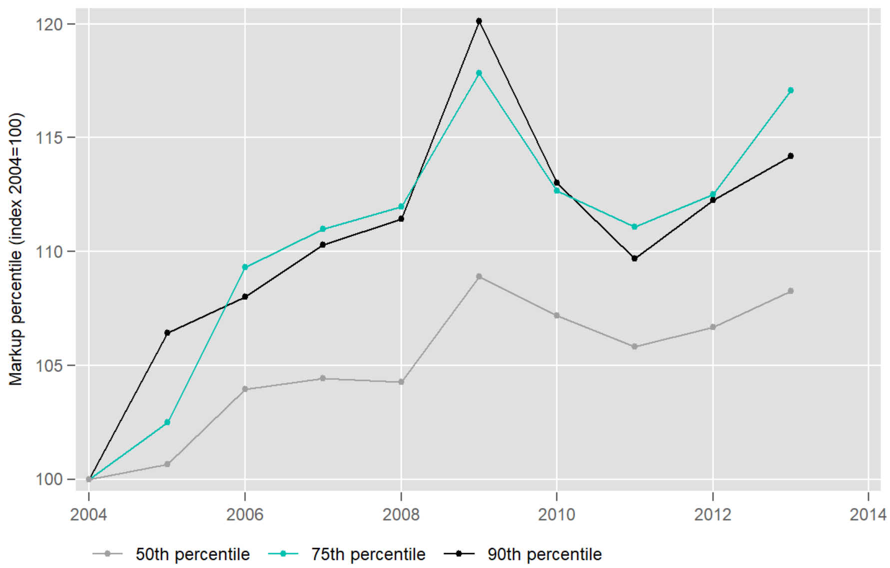
Note. The figure displays the evolution of average firm-level markups from 2004 to 2013 by ISIC Rev. 4 industries, where the average markup is weighted by firm sales. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, own calculations.

The automotive industry (Panel a) experienced a considerable rise in the robot density between 2004 and 2013, while there was virtually no change in the manufacture of other non-metallic mineral products such as ceramic and glass products (Panel b). In the more robotized automotive industry, the 90th percentile of the TFP distribution has dis-proportionally increased compared to the 75th percentile and the median. In contrast, in the non-robotized ceramic and glass industry, the upper decile has grown by less than the median productivity.

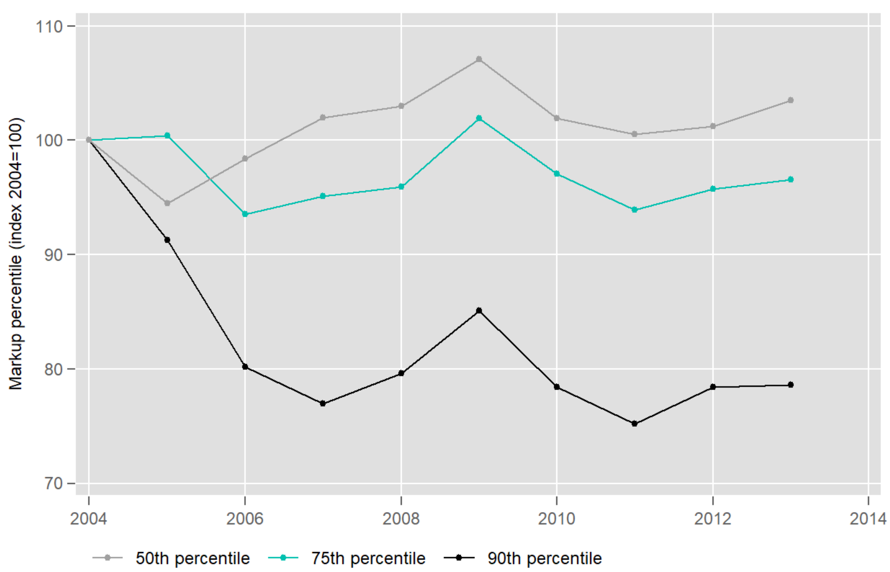
Those two examples, therefore, suggest that the emergence of the superstar pattern in productivity growth (higher growth in firms that are already highly productive) coincides with a higher degree of robotization, and we will investigate this link more closely below.

The industry-level evolution of average markups is displayed in Figure 4, where the average markup is weighted by firm sales.[31] In line with Weche and Wambach (2018), we also find markups have been falling in the course of the financial crisis in several industries. Since 2010 or so, however, average markups tend to be increasing in almost all European manufacturing industries.

[31] As in Figure 2, the sample includes firms which are present in the data for at least five years.



(a) Motor vehicles



(b) Electronics

Figure 5: Evolution of markup percentiles.

Note. The figure displays the evolution of different percentiles of the markup distribution from 2004 to 2013, exemplarily for two manufacturing industries which are characterized by a different degree of robotization: motor vehicles (high increase in the robot density, Panel a) and electronics (low increase in the robot density, Panel b). The percentiles are calculated using sales weighted firm-level markups. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, own calculations.

Figure 5 goes beyond the average and shows the evolution of markup percentiles, again for the two industries that were highlighted before. In the automotive industry, where the number of robots per thousand workers has increased substantially, the 75th and the 90th percentiles of markups have grown more than the median (Panel a). In contrast, this pattern does not hold true for the non-robotized electronics industry where especially the 90th percentile has strongly decreased in the first years of the sample (Panel b). Again, we will investigate the link between robotization and shifts in the within-industry distribution of firm-level markups more closely below.

4.2 Robots and the distribution of firm-level productivity and markups

This subsection presents the results on the impact of robots on TFP and markups. As outlined in Section 3.2, the regression equation is estimated in differences, as we are interested in the effect of a change in the robot stock on the change in firm-level outcomes. The estimation sample covers firm observations with non-missing data on the variables of interest (i.e., TFP, markups, sales, and the labor share), both in the first and in the last year of any five-year period between 2004 and 2013.

Table 2 shows the results for TFP. In the first two columns, we present the average effect of robots controlling for country and year fixed effects, and including either the baseline TFP level (column 1) or dummy variables for the quintiles of baseline TFP within country-industry-year cells (column 2). The coefficients are close to zero and statistically insignificant at conventional levels. This suggests that the average productivity across firms does not change when an industry gets more robotized, ceteris paribus.

Columns (3) to (6) take a closer look how a change in the robot stock affects the different parts of the productivity distribution within an industry. To do so, we interact the change in robots with quintile or decile dummies based on the distribution of firm TFP at the beginning of the period. The full specification is presented in the fifth column, where we control for other changes at the industry level (for instance, other technologies and globalization) as well as for baseline industry characteristics. It reveals a rise in TFP for the top 20% of firms with highest initial productivity, but an insignificant effect on the other firms in an industry. The evidence is corroborated by the estimates in column (6), where TFP deciles are exploited to allow for a more fine-grained analysis. There we observe the highest productivity gains for a set of firms at the productivity frontier – the top 10% most productive firms within a country, industry, and year –, which are able to increase their already high productivity even further.

Table 3 reports the results for markups. While the average effect is again not statistically significant, the interaction terms with quintiles (column 5) and deciles (column 6) – calculated based on a firm's markup at the beginning of the period in that country and industry – show considerable

Table 2: The effects of robots on TFP.

	Dependent variable: $\triangle_5$ ln(TFP)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle_5$ ln(Robots)	-0.0074	0.0059				
	(0.006)	(0.005)				
$\triangle_5$ ln(Robots) x Quin1			-0.0030	-0.0046	-0.0025	
			(0.005)	(0.005)	(0.004)	
x Quin2			0.0036	0.0020	0.0041	
			(0.005)	(0.005)	(0.004)	
x Quin3			0.0049	0.0033	0.0054	
			(0.005)	(0.005)	(0.005)	
x Quin4			0.0068	0.0051	0.0073	
			(0.005)	(0.005)	(0.005)	
x Quin5			0.0176**	0.0160**	0.0183**	
			(0.008)	(0.008)	(0.008)	
x Dec1						-0.0072
						(0.005)
x Dec2						0.0024
						(0.004)
x Dec3						0.0026
						(0.004)
x Dec4						0.0058
						(0.004)
x Dec5						0.0041
						(0.005)
x Dec6						0.0068
						(0.005)
x Dec7						0.0058
						(0.005)
x Dec8						0.0090*
						(0.005)
x Dec9						0.0128*
						(0.007)
x Dec10						0.0241**
						(0.011)
Country, year dummies	✓	✓	✓	✓	✓	✓
$\triangle_5$ other technologies				✓	✓	✓
$\triangle_5$ other industry changes					✓	✓
Industry controls in $t-5$					✓	✓
Dep. variable in $t-5$	✓					
Dummies for quintiles		✓	✓	✓	✓	
Dummies for deciles						✓

Note. Based on 110,710 firm observations. We estimate the effect of the log change in the industry-level robot stock on the log change in firm-level TFP by OLS using overlapping five-year differences. Column (1) includes the baseline log TFP as well as country and year dummies. In column (2), instead of the baseline log TFP level, quintile dummy variables are included. For instance, $Quin2 = 1$ if $ln(TFP)_{ijct-5} > p20$ and $ln(TFP)_{ijct-5} \leq p40$ and 0 otherwise, where $p20$ and $p40$ represent the first and second quintiles of firm-level TFP within a country c, industry j, and year t. In the columns (3)–(6), we estimate heterogeneous effects by interacting the change in robots with the dummy variables for the quintiles (columns 3–5) or deciles (column 6) of baseline TFP. Column (4) adds the log changes in investments in ICT, R&D, and computer software and databases, respectively. Column (5) further includes other industry controls: the log changes in imports and exports, the change in the market share of foreign-owned firms, the change in the capital-to-labor ratio, as well as baseline log wages and the capital-to-labor ratio. Standard errors clustered by country x industry in parentheses. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

heterogeneity between firms. A large fraction of firms actually decrease their markups on average when more robots are installed. At the same time, we observe a rise in markups for the top 10% of firms with highest initial markups.

The empirical observation that high markup firms are able to charge even higher markups while the opposite is true for less profitable firms has profound implications for the distribution of market power within industries. It gets more skewed towards firms charging high markups, which is in line with the evolution described in De Loecker and Eeckhout (2017) and Calligaris et al. (2018).

The results presented so far indicate that the expansion of industrial robots as a form of technological change dis-proportionally benefits the "best firms" within an industry, with the highest productivity and markups, which are able to get even more productive and charge higher markups.

One explanation for these findings is related to the returns of technology adoption, as studied in the context of innovation-induced gains from trade liberalization (e.g.: Lileeva and Trefler, 2010; Bustos, 2011; Bertschek et al., 2015). A firm will invest in a productivity-enhancing technology if the expected gains from a reduction in marginal costs of production are greater than the fixed costs of adoption. Since the benefit of technology adoption increases in revenues, the (cost-intensive) investment in industrial robots is most profitable for firms which expect high revenues after robot installation. Highly productive firms, which are able to set prices well above marginal costs, might therefore especially forge ahead in and benefit from robotization. This explanation is also consistent with the results in Section 5, where we show that only large firms in terms of sales are able to boost sales further when their industry gets more robotized.

Table A.2 in the appendix demonstrates that the estimated effects of robots on the distribution of firm-level productivity and markups within industries are robust when allowing for heterogeneity in the impact of the other technology and innovation measures in the data (i.e., ICT, R&D, and computer software and databases). In the columns (1) and (3), we replicate the results of the full specifications in column (5) of Table 2 and Table 3 respectively. Columns (2) and (4) show that the impact of robots remains very similar when adding interaction terms between the changes in investments in the other technology types and the dummy variables for the quintiles of baseline TFP respectively markups. Moreover, these results illustrate that the effects on TFP and markups differ across the technology and innovation measures. For ICT, software and databases, and R&D – in contrast to industrial robots – we do not identify a superstar phenomenon, in the sense that they do not dis-proportionally benefit the very productive firms and those which already enjoy the highest market power. One explanation may be that ICT as well as software and databases are nowadays already widely used since the fixed costs of adoption have fallen dramatically during the past decades. In addition, these technologies might have a bigger impact in service industries than

Table 3: The effects of robots on markups.

	Dependent variable: $\triangle_5$ ln(Markup)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle_5$ ln(Robots)	-0.0186	-0.0139				
	(0.012)	(0.012)				
$\triangle_5$ ln(Robots) x Quin1			-0.0232*	-0.0224*	-0.0272**	
			(0.014)	(0.013)	(0.010)	
x Quin2			-0.0277**	-0.0269**	-0.0317***	
			(0.014)	(0.012)	(0.010)	
x Quin3			-0.0181	-0.0172	-0.0219**	
			(0.013)	(0.012)	(0.010)	
x Quin4			-0.0188	-0.0179	-0.0228**	
			(0.013)	(0.011)	(0.009)	
x Quin5			0.0188*	0.0197*	0.0147*	
			(0.011)	(0.010)	(0.008)	
x Dec1						-0.0285***
						(0.010)
x Dec2						-0.0257**
						(0.011)
x Dec3						-0.0326***
						(0.010)
x Dec4						-0.0306***
						(0.011)
x Dec5						-0.0239**
						(0.011)
x Dec6						-0.0198**
						(0.009)
x Dec7						-0.0258**
						(0.010)
x Dec8						-0.0195**
						(0.009)
x Dec9						-0.0119
						(0.009)
x Dec10						0.0422***
						(0.011)
Country, year dummies	✓	✓	✓	✓	✓	✓
$\triangle_5$ other technologies				✓	✓	✓
$\triangle_5$ other industry changes					✓	✓
Industry controls in $t-5$					✓	✓
Dep. variable in $t-5$	✓					
Dummies for quintiles		✓	✓	✓	✓	
Dummies for deciles						✓

Note. Based on 110,710 firm observations. We are interested in the impact of the log change in the industry-level robot stock on the log change in firm-level markups. The regression equations are estimated by OLS using overlapping five-year differences. The specification in column (1) controls for the baseline log markup in period $t-5$ as well as for country and year dummies. In column (2), instead of the baseline markup, dummy variables for the quintiles of baseline markups within country-industry-year cells are included. In the columns (3)–(6), we estimate heterogeneous effects by interacting the change in robots with the dummy variables for the markup quintiles (columns 3–5) or deciles (column 6). Column (4) adds the log changes in other technologies, and column (5) further includes other industry changes as well as initial industry characteristics. See Table 2 for a detailed description of control variables. Standard errors clustered by country x industry in parentheses. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

in our sample of manufacturing firms.

4.3 Robustness checks

In this subsection, we discuss several robustness checks and how they affect the main results. The checks are applied to the heterogeneous effects specification, where the log change in robots is interacted with quintile dummies. The results are presented in Table 4.

Robot density The first robustness check concerns the construction of the main variable of interest, the change in robots. A small number of papers have already exploited the robot data set from the IFR to mainly analyze labor market effects (e.g.: Acemoglu and Restrepo, 2017; Dauth et al., 2018), but also a broader set of outcomes including productivity (Graetz and Michaels, 2018). These contributions estimate the effect of robots by relying on the change in the robot density, which is defined as the change in robots per thousand workers in the baseline year. We do not use this measure in our main specification as the baseline regression equation (11) could no longer be derived from the productivity process assumed within the context of the production function estimation (at least not when utilizing baseline employment for normalization). Nevertheless, we use the change in the robot density as an alternative measure, in order to show that our results are consistent with the previous literature. The estimates in column (1) for TFP (Panel A) and for markups (Panel B) confirm our main findings as they clarify the dis-proportional impact of robots on the superstar firms in an industry.[32] Graetz and Michaels (2018) analyze the long-run impact of robots on average industry-level TFP and find a positive and significant effect using differences between 1993 and 2007 (see their Table 2). While the average influence of robots on TFP is small and statistically insignificant in our setting using five-year differences, the positive outcome for high productive firms is roughly in the same ballpark as in Graetz and Michaels (2018).[33]

Industry-specific trends Another concern are industry-specific trends that are correlated both with robotization and with changes in productivity and market power. We already try to mitigate this concern by controlling for a set of concurrent developments at the industry-level such as other technologies, globalization variables, and the capital-to-labor ratio. A more rigorous approach is to include industry dummies in order to allow for industry-specific trends in the difference equation. Column (2) reports the estimated coefficients. Even though we can exploit less variation in the data to identify the effects, the results hold as they are of similar magnitude and highly significant.

[32] Note that we also employ the robot density instead of the log robot stock in the production function estimation. The estimated production function coefficients are reported in Appendix Table A.3.

[33] The robustness checks for the baseline models without heterogeneous effects are available upon request. Bear in mind that their measure of robot adoption is divided by one hundred

Table 4: Robustness checks.

	Density	Ind. dummies	Not lagged	$\triangle_4$	$\triangle_3$	Translog	IV, set A	IV, set B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
[A] $\triangle$ ln(TFP)								
$\triangle$ Robots x Quin1	-0.0009*	-0.0068	0.0009	-0.0101**	-0.0166***	0.0006	-0.0014	0.0003
	(0.000)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.008)	(0.006)
x Quin2	0.0000	-0.0002	0.0056	-0.0038	-0.0127***	0.0053	0.0036	0.0054
	(0.001)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.008)	(0.007)
x Quin3	0.0007	0.0010	0.0069	0.0007	-0.0056	0.0079	0.0040	0.0057
	(0.001)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)	(0.007)
x Quin4	0.0005	0.0030	0.0087*	0.0004	-0.0068	0.0085*	0.0055	0.0075
	(0.001)	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.007)	(0.006)
x Quin5	0.0025**	0.0140**	0.0201**	0.0122	0.0036	0.0101*	0.0117	0.0167
	(0.001)	(0.007)	(0.008)	(0.008)	(0.007)	(0.006)	(0.014)	(0.012)
[B] $\triangle$ ln(Markup)								
$\triangle$ Robots x Quin1	-0.0032***	-0.0215**	-0.0247**	-0.0273***	-0.0257***	-0.0223***	-0.0120	-0.0179
	(0.001)	(0.009)	(0.011)	(0.009)	(0.009)	(0.008)	(0.012)	(0.011)
x Quin2	-0.0025**	-0.0260***	-0.0290***	-0.0260***	-0.0224***	-0.0154**	-0.0232*	-0.0265**
	(0.001)	(0.008)	(0.010)	(0.009)	(0.008)	(0.006)	(0.012)	(0.012)
x Quin3	-0.0025**	-0.0164**	-0.0166*	-0.0153**	-0.0124**	-0.0125**	-0.0170	-0.0189*
	(0.001)	(0.008)	(0.010)	(0.007)	(0.006)	(0.005)	(0.011)	(0.011)
x Quin4	-0.0021*	-0.0173**	-0.0175*	-0.0030	-0.0053	-0.0086	-0.0187*	-0.0177
	(0.001)	(0.008)	(0.010)	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)
x Quin5	0.0022	0.0202**	0.0168**	0.0305***	0.0287***	-0.0067	0.0081	0.0142
	(0.001)	(0.008)	(0.008)	(0.008)	(0.009)	(0.006)	(0.013)	(0.011)
N	110,727	110,710	114,140	171,570	228,313	109,679	110,710	110,710

Note. Based on N firm observations. This table presents robustness checks for the heterogeneous effects of robots on TFP (Panel A) and on markups (Panel B), based on the specifications in column (5) of Table 2 respectively Table 3. Column (1) uses the change in the robot density – the change in robots per thousand workers – instead of the log change in robots as the main variable of interest. In column (2), we add industry dummies to control for industry trends. Columns (3)–(5) check the robustness with regard to timing issues, by not lagging the log change in robots (column 3), and by using four-year (column 4) and three-year (column 5) instead of five-year differences. Column (6) assumes a translog rather than a Cobb-Douglas production function in estimating TFP and markups. In columns (7) and (8), the industry-level robot stock in the sample countries is instrumented with robot installations in the US and the UK (set A), or in the US, the UK, Norway, Belgium, Portugal, and Austria (set B), and over-identified models are estimated by 2SLS. Standard errors clustered by country x industry in parentheses. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

Timing The next set of robustness checks refers to timing issues. First, in our main specification, the change in robots is lagged by one period, due to the assumptions on the productivity process (see Equation 10). In column (3), we instead use the same time period in constructing the change in outcomes and the change in the robot stock. The results remain similar, so the main findings do not hinge on the assumed lag structure.[34] Second, rather than estimating the regression equation in five-year differences, we try changes of four (column 4) and three years (column 5). The effects on markups are highly significant and emphasize the heterogeneous impact of robots. The estimates for TFP point into the same direction, but are smaller in magnitude and less significant.

Translog production function The results discussed so far assume a Cobb-Douglas gross output production function in estimating TFP and markups. In order to allow for more flexibility, we consider a translog production function:

$$\begin{aligned} q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{kl} k_{it} l_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it} \\ + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{klm} k_{it} l_{it} m_{it} + \omega_{it} + \epsilon_{it}, \end{aligned} \tag{13}$$

where output may depend non-linearly on input factors. It is more flexible, as output elasticities are not specific to industries but vary across firms and time. In addition, a firm's markup (within an industry) does not only depend on its material share in total sales, but also on the firm-specific output elasticity of materials. A drawback of this specification, as explained in Section 3.1, is the potential output price bias that is more relevant than in the Cobb-Douglas case. In addition, the high number of parameters to be estimated may lead to collinearity problems. Appendix Table A.4 reports the estimated production function coefficients, which are broadly consistent with the ones obtained when assuming a Cobb-Douglas production function. After recalculating markups and TFP, the effects of robots are presented in column (6) of Table 4. The results confirm our main findings, with the exception of the impact on high markup firms. While we still observe that a change in robots is associated with decreasing markups for low and medium markup firms, we do not identify a positive effect for firms with initially high markups. Nevertheless, it is consistent with the main findings insofar, as robotization does not affect all firms in an industry equally.

Instruments We identify the effects of robots on industry-level productivity and markups by carefully controlling for various confounding factors. Above all, we account for other types of technology

[34]In this specification, we stick to the estimated TFP and markups that are based on the production function estimation where current productivity is a function of the lagged change in robots. In another robustness check, we instead incorporate the current change in robots and run again the specification in column (3) of Table 4. The results are very similar and are available upon request. Note that we also do not lag the other industry-level changes in this specification.

and innovation that may be correlated with robot densification and at the same time affect productivity or markups. Furthermore, we consider additional concurrent developments at the industry level and baseline industry characteristics, as well as country, time, and industry trends. And by estimating the regression equation in differences, unobserved confounders which are constant over the considered period (five years in the main specification) cannot bias the results. Nevertheless, one might still worry about other omitted variables, measurement error, or reverse causality. For example, concerning the latter, it might be that the implementation of robots is the result of an increasing presence of superstar firms, and not the other way round. To address these concerns, we adopt an IV approach in the spirit of Acemoglu and Restrepo (2017), who employ robot adoptions across industries in European countries as an instrument for robotization in the US.[35]

We instrument the industry-level robot stock in the six European countries with robot installations in the US and the United Kingdom (UK), and estimate an over-identified model using two-stage least squares (2SLS). The idea of this instrumental strategy is to capture the component of robot adoption that is due to a general technology trend, thus eliminating unobserved domestic shocks. In another specification, we additionally exploit robot installations in Norway, Belgium, Portugal, and Austria, as these are the countries for which we have comprehensive robot data at the industry level from 2004 onwards. The drawback of the latter set of instruments is that some of these countries are direct neighbors of the sample countries, and hence the exogeneity assumption might be violated.

Column (7) of Table 4 summarizes the results of the IV specification using industry-level robots in the US and the UK as instruments (instrument set A). In line with the OLS estimates, we find that an increasing number of robots benefit the most productive and the most profitable firms. Column (8) exploits the whole set of possible instrument countries (instrument set B), and the results are similar. Appendix Table A.5 presents the first stage results. The F-Tests on excluded instruments (Panel A) and the Kleibergen-Paap weak identification tests (Panel B) suggest that we do not need to worry about weak instruments for the instrument set B, but we may have some concerns for the instrument set A where the F-Statistics for the joint significance of instruments in the first stage are below 10. In Panel C, we implement the same test statistics for the baseline specification, i.e., for the model without allowing for heterogeneous effects of robots. The results are reassuring as the excluded instruments are jointly highly significant for both instrument sets, and the Kleibergen-Paap statistics are above the critical values for a 10% maximal IV bias of the weak identification test proposed by Stock and Yogo (2005).[36]

[35]This IV strategy has also been implemented by Dauth et al. (2018) to analyze the labor market effects of robots in Germany.

[36]The critical values for a 10% maximal IV bias are 19.93 for two instrumental variables and 29.18 for six instrumental variables (Stock and Yogo, 2005). Note that the Stock-Yogo critical values are not available for five endogenous regressors.

5 Industry concentration and the labor share

This section presents the results on the impact of robots on industry concentration and the labor share. First, we estimate the effects of robots on firm-level sales in the same way as in Section 4 for productivity and markups. In particular, we are interested in the heterogeneity with regard to initial levels of firm sales within country-industry-year cells. Second, we investigate the effects of robots on the industry-level labor share. The focus lies on the reallocation mechanism proposed by Autor et al. (2017a,b), i.e., the increased concentration of sales in firms with a small labor share.

Table 5 reports the results for sales. In the first two columns, we present the average impact of robots, controlling for country and year fixed effects. The estimated coefficients are positive and significant, suggesting that average sales increase when an industry gets more robotized, ceteris paribus. However, the average effects are driven by large firms with high sales, as shown in the full specifications in the columns (5) and (6). These firms are able to boost sales further, while small firms experience a significant decline in their sales.[37] This finding points out the potential of a recent form of automation technology in increasing sales concentration within industries and thereby triggering *winner take most* dynamics, consistent with Bessen (2017).

What is the role of rising sales concentration in the falling labor share observed in many countries over the last decades, and do industrial robots contribute to this development? In Panel A of Table 6, we display the average firm-level labor share (i.e., total labor costs over sales) by sales quintiles which are defined within a country, industry, and year. The average labor share decreases as a function of sales: while the lowest sales quintile pays on average 28% of their sales to workers, it is only 16% for the highest quintile. Hence, if firms with already high sales manage to disproportionally increase their sales further, the industry-level labor share will decrease because of the reallocation of production towards these low labor share firms. Since we have identified this pattern of sales in Table 5 as a result of industry-level robotization, we analyze in Panel B of Table 6 the impact of robots on the aggregate labor share. In doing so, we rely on the baseline specification (see Equation 11) where the outcome of interest is the five-year change in the labor share at the country-industry-year level. The aggregate labor share is calculated either based on unweighted averages (columns 1–3) or on averages weighted by firm sales (columns 4–6). The OLS regression in column (1) shows that the unweighted labor share does not decline significantly when more robots are installed in an industry. In contrast, we do observe a significant drop in the sales-weighted labor share (column 4). These results hold when the industry-level robot stock is instrumented with robot installations in the US and the UK (columns 2 and 5), or additionally in Norway, Belgium, Portugal, and Austria

[37] See Appendix Table A.6 for the robustness checks with regard to the heterogeneous effects of robots on sales, and Appendix Table A.7 for the first stage results of the IV estimations.

Table 5: The effects of robots on sales.

	Dependent variable: $\triangle_5$ ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle_5$ ln(Robots)	0.0562**	0.0417*				
	(0.024)	(0.022)				
$\triangle_5$ ln(Robots) x Quin1			-0.0132	-0.0152	-0.0390**	
			(0.018)	(0.019)	(0.017)	
x Quin2			0.0328	0.0308	0.0072	
			(0.022)	(0.023)	(0.018)	
x Quin3			0.0502*	0.0482*	0.0250	
			(0.027)	(0.027)	(0.023)	
x Quin4			0.0696**	0.0675**	0.0447**	
			(0.027)	(0.027)	(0.022)	
x Quin5			0.0697**	0.0677**	0.0449*	
			(0.027)	(0.027)	(0.025)	
x Dec1						-0.0720***
						(0.021)
x Dec2						-0.0054
						(0.019)
x Dec3						0.0058
						(0.019)
x Dec4						0.0087
						(0.018)
x Dec5						0.0206
						(0.023)
x Dec6						0.0294
						(0.023)
x Dec7						0.0431*
						(0.023)
x Dec8						0.0463**
						(0.021)
x Dec9						0.0508**
						(0.023)
x Dec10						0.0391
						(0.030)
Country, year dummies	✓	✓	✓	✓	✓	✓
$\triangle_5$ other technologies				✓	✓	✓
$\triangle_5$ other industry changes					✓	✓
Industry controls in $t-5$					✓	✓
Dep. variable in $t-5$	✓					
Dummies for quintiles		✓	✓	✓	✓	
Dummies for deciles						✓

Note. Based on 110,710 firm observations. We are interested in the impact of the log change in the industry-level robot stock on the log change in firm-level sales. The regression equations are estimated by OLS using overlapping five-year differences. The specification in column (1) controls for baseline log sales in period $t-5$ as well as for country and year dummies. In column (2), instead of baseline sales, dummy variables for the quintiles of baseline sales within country-industry-year cells are included. In the columns (3)–(6), we estimate heterogeneous effects by interacting the change in robots with the dummy variables for the sales quintiles (columns 3–5) or deciles (column 6). Column (4) adds the log changes in other technologies, and column (5) further includes other industry changes as well as initial industry characteristics. See Table 2 for a detailed description of control variables. Standard errors clustered by country x industry in parentheses. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

Table 6: The effects of robots on the labor share.

[A] Firm-level labor share by sales quintiles

	Quin1	Quin2	Quin3	Quin4	Quin5
Mean	0.28	0.24	0.21	0.18	0.16
Std. dev.	0.13	0.12	0.11	0.10	0.09
N	22,282	22,141	22,145	22,140	22,002

[B] Regressions at the industry level

	$\triangle_5$ Labor share					
	Unweighted			Weighted by firm sales		
	(1) OLS	(2) IV, set A	(3) IV, set B	(4) OLS	(5) IV, set A	(6) IV, set B
$\triangle_5$ ln(Robots)	-0.0022	-0.0020	-0.0018	-0.0041**	-0.0061**	-0.0050**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
N	326	326	326	326	326	326
Country, year dummies	✓	✓	✓	✓	✓	✓
$\triangle_5$ other technologies	✓	✓	✓	✓	✓	✓
$\triangle_5$ other industry changes	✓	✓	✓	✓	✓	✓
Industry controls in $t-5$	✓	✓	✓	✓	✓	✓
Dep. variable in $t-5$	✓	✓	✓	✓	✓	✓

Note. Number of observations N. The firm-level labor share is defined as total labor costs over sales. Panel A presents summary statistics of the labor share by sales quintiles, where $Quin1$ represents the first quintile group. As defined in Table 5, firms are classified into five groups based on their baseline sales within a country, industry, and year. In Panel B, the labor share is aggregated to the country-industry-year level, using either unweighted averages or averages weighted by firm sales. We are interested in the impact of the (one-period lagged) log change in the industry-level robot stock on the change in the unweighted (columns 1-3) and weighted (columns 4-6) industry-level labor share. The regression equations are estimated using (overlapping) five-year differences. Columns (1) and (4) present OLS estimations. Columns (2)-(3) as well as columns (5)-(6) present IV estimations where over-identified models are estimated using 2SLS. The industry-level robot stock in the sample countries is instrumented with robot installations in the US and the UK (set A), or in the US, the UK, Norway, Belgium, Portugal, and Austria (set B). The regressions include the full set of control variables as described in Table 2. Standard errors are clustered by country x industry in parentheses. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

(columns 3 and 6).[38] The estimated effects of robots on industry concentration and the labor share are consistent with the evidence in Autor et al. (2017a,b). We show that one potential explanation for the falling labor income share is the growing use of industrial robots, which allows large firms with a low labor share to increase their sales further, thus decreasing the aggregate labor share.

6 Conclusion

The rapid pace of technological change raises concerns about the rise of superstar firms, which increasingly dominate markets. But empirical evidence for this superstar phenomenon, and in par-

[38] See Appendix Table A.8 for the corresponding first stage results. In all models, the excluded instruments are jointly highly significant, and the Kleibergen-Paap statistics are above the critical values for a 10% maximal IV bias of the weak identification test proposed by Stock and Yogo (2005). These critical values are 19.93 for two instrumental variables and 29.18 for six instrumental variables (Stock and Yogo, 2005).

ticular about the role of technology in shaping its emergence, is still in its infant stages.

In this paper, we have examined the impact of industrial robots – a recent form of a digital automation technology – on the distribution of firm performance within industries. We exploit data for six European countries from 2004 to 2013, and calculate heterogeneous effects by interacting the change in the industry-level robot stock with baseline firm performance within country-industry-year cells. The results indicate that an increase in robots implies a rise in firms' productivity and markups for those firms with initially high productivity and profitability, respectively, but has an insignificant or even negative effect on the other firms in an industry. In addition, we show that large firms in more robot exposed industries are able to boost their sales, while small firms experience a significant decline. This reallocation of market shares tends to depress the aggregate labor share of income, because the large and productive firms tend to exhibit lower firm-specific labor cost shares.

Robotization thus seems to dis-proportionally benefit the best firms in an industry, and thereby contributes to several economic trends observed over the last decades, such as the divergence of productivity and markups as well as shifts in the functional income distribution away from labor and towards capital and profit earnings.

An increasing dispersion of productivity and markups across firms has broader implications for society. As high productive firms typically pay higher wages in absolute terms, it may further push up the wages of top earners in these firms, leading to a widening dispersion in household incomes.[39] Perhaps even more important, it may be firm and capital owners who benefit most from the recent technology wave. Dauth et al. (2018) provide suggestive empirical evidence that robotization increases productivity but not average wages. Our analysis emphasizes a key channel through which industrial robots may affect the aggregate labor share: the reallocation of market shares towards successful firms which tend to pay better in absolute terms, but at the same time are able to keep a larger share of revenue as profits.

These economic trends call for an economic policy that supports productivity growth across the broader economy, not just among top firms at the technological frontier, and distributes the rents created by new technologies more equally. At the moment, asset ownership and the entitlement to profit earnings is highly concentrated and unequally distributed. The effects of new technologies on the functional income distribution (higher profit and lower labor income shares) then also imply higher inequality in the personal income distribution. Useful policy steps to counteract those distributional implications could be measures to foster profit-sharing, employee stock options, or similar arrangements. Those instruments would aim for a wider distribution of asset ownership in the society at large.

[39] See the discussion in Haldane (2017), and the empirical evidence in Berlingieri et al. (2017) who show that the divergence of wages is linked to increasing differences between high and low productive firms.

Our paper also lays out fruitful avenues for future research. This study takes a first step by providing novel evidence on the heterogeneous effects of one specific new technology (robots) on firm performance, by observing installations of industrial robots at the industry level. More research on other types of recent automation technologies is needed in order to comprehensively understand the effects. So far, there is a lack of firm-level data on the use of robotics and artificial intelligence. Data at the firm level would greatly enhance the understanding of how these technologies contribute to firm-level productivity, which types of firms invest and what is the role of the market structure, and how adoption affects firm strategies (Raj and Seamans, 2019). For future research, it might also be interesting to understand how new technologies favor these superstar firms. For example, is it slowing technological diffusion from frontier to laggard firms, or rather better worker-firm matching in the sense that highly productive firms attract more skilled workers that are better in adapting to technological advancements? Relatedly, future research might put emphasis on how technological change increases productivity, in the sense whether it is factor-neutral or biased towards a specific factor. While the productivity and industrial organization literature typically assumes that technology is Hicks-neutral, Doraszelski and Jaumandreu (2018) show a labor-augmenting component using data on firms' R&D expenditures in the Spanish manufacturing sector. With firm-level data on technology adoption at hand, this may be an important line of research to follow.

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A Appendix

A.1 Data Appendix

SITC-ISIC cross-walk

In order to link the Comtrade data with the robot data from the IFR, we need to harmonize two different industry classifications. The Comtrade data is provided according to the SITC Rev. 3 industry classification, while the IFR data is made available according to the ISIC Rev. 4 classification. Since the latter is aggregated at the 2-digit level (with some industries even further aggregated, see Table A.1), the breakdown by 2-digit industries is sufficient for our purposes. Hence, as the ISIC Rev. 4 industry classification is equivalent to NACE Rev. 2 industries at the 2-digit level, we convert the SITC Rev. 3 to the NACE Rev. 2 industry classification. This involves three cross-walks: NACE Rev. 1.1 to NACE Rev. 2 (cross-walk A), NACE Rev. 1 to NACE Rev. 1.1 (cross-walk B), and SITC Rev. 3 to NACE Rev. 1 (cross-walk C). Cross-walk C is provided by the World Bank (`https://wits.worldbank.org/product_concordance.html`), while cross-walks A and B are given by Eurostat
(`http://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL&StrLanguageCode=EN&IntCurrentPage=10`).

Cross-walks A and B are provided at the 4-digit industry level. However, since the cross-walk C relates the SITC Rev. 3 industry codes to 3-digit NACE Rev. 1 industries, we also aggregate the industries in cross-walks A and B to the 3-digit level. After doing this, cross-walk C is merged to cross-walk B, and the result is in turn merged to cross-walk A. The resulting cross-walk between the SITC Rev. 3 and the NACE Rev. 2 classifications includes ambiguous cases, where one SITC Rev. 3 industry is assigned to several NACE Rev. 2 industries. In order to tackle this problem of ambiguous cases, we use employment data to approximate the size of each NACE industry, and construct the employment share of each NACE code in all assigned codes as weights. More specifically, we employ data on the industry level number of employees from Eurostat SBS in 2008, the year when the NACE Rev. 2 was introduced. Since the employment data is not comprehensively available across industries for all countries in our sample, average weights are calculated by relying on data from Germany, Spain, and Italy. In a last step, the trade values at the 3-digit NACE level are aggregated to 2-digit industries (and are therefore equivalent to ISIC Rev. 4 industries). Please note that for some industries no employment data is available, namely for the NACE Rev. 2 industry groups A (agriculture, forestry and fishing), O (public administration and defence), P (education), Q (human health and social work activities), R (arts, entertainment and recreation), T (activities of households as employers), and U (activities of extraterritorial organisations and bodies). We consider this as a rather minor issue, as these are not the industries for which we would expect much trade.

A.2 Appendix Tables

Table A.1: Estimated production function coefficients.

		Production function coefficients			
Industry	Code	Labor	Materials	Capital	RTS
Food products, beverages, tobacco	10-12	0.23	0.68	0.10	1.00
Textiles, leather, wearing apparel	13-15	0.41	0.50	0.06	0.96
Wood and wood products	16	0.32	0.61	0.08	1.01
Paper and paper products	17-18	0.41	0.50	0.07	0.98
Other chemical products	19-20	0.29	0.63	0.10	1.01
Pharmaceuticals, cosmetics	21	0.35	0.60	0.03	0.99
Rubber and plastic products	22	0.24	0.65	0.07	0.97
Other non-metallic mineral products	23	0.36	0.56	0.10	1.02
Basic metals	24	0.31	0.62	0.05	0.99
Fabricated metals	25	0.44	0.45	0.10	0.99
Electronics	26-27	0.38	0.56	0.06	1.00
Industrial machinery	28	0.38	0.54	0.07	0.99
Motor vehicles	29	0.32	0.58	0.08	0.99
Other transport equipment	30	0.35	0.57	0.05	0.97

Note. These are the results of the production function estimation, assuming a Cobb-Douglas production technology, and including the (lagged) log change in industrial robots in the productivity process. The industries are classified according to ISIC Rev. 4. Returns to scale RTS. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, own calculations.

Table A.2: Heterogeneous effects of other technology and innovation measures.

	$\triangle_5$ ln(TFP)		$\triangle_5$ ln(Markup)	
	(1)	(2)	(3)	(4)
$\triangle_5$ ln(Robots) x Quin1	-0.0025	-0.0011	-0.0272**	-0.0280***
	(0.004)	(0.004)	(0.010)	(0.010)
x Quin2	0.0041	0.0051	-0.0317***	-0.0316***
	(0.004)	(0.004)	(0.010)	(0.010)
x Quin3	0.0054	0.0058	-0.0219**	-0.0218**
	(0.005)	(0.005)	(0.010)	(0.010)
x Quin4	0.0073	0.0069	-0.0228**	-0.0228**
	(0.005)	(0.005)	(0.009)	(0.009)
x Quin5	0.0183**	0.0157**	0.0147*	0.0154*
	(0.008)	(0.007)	(0.008)	(0.009)
$\triangle_5$ ln(ICT) x Quin1		-0.0044		0.0132**
		(0.005)		(0.006)
x Quin2		-0.0042		0.0078
		(0.004)		(0.006)
x Quin3		-0.0014		0.0059
		(0.004)		(0.007)
x Quin4		0.0026		0.0105
		(0.004)		(0.007)
x Quin5		0.0121		-0.0031
		(0.008)		(0.008)
$\triangle_5$ ln(R&D) x Quin1		-0.0007		0.0067
		(0.007)		(0.015)
x Quin2		-0.0075		0.0161
		(0.007)		(0.018)
x Quin3		-0.0138*		0.0147
		(0.007)		(0.016)
x Quin4		-0.0236***		0.0175
		(0.007)		(0.017)
x Quin5		-0.0487***		0.0168
		(0.011)		(0.019)
$\triangle_5$ ln(Software) x Quin1		-0.0032		0.0133
		(0.008)		(0.013)
x Quin2		-0.0089		0.0080
		(0.008)		(0.011)
x Quin3		-0.0098		0.0075
		(0.007)		(0.013)
x Quin4		-0.0132**		0.0155*
		(0.006)		(0.009)
x Quin5		-0.0279***		-0.0069
		(0.008)		(0.012)
Country, year dummies	✓	✓	✓	✓
$\triangle_5$ other technologies	✓		✓	
$\triangle_5$ other industry changes	✓	✓	✓	✓
Industry controls in $t-5$	✓	✓	✓	✓
Dummies for quintiles	✓	✓	✓	✓

Note. Based on 110,710 firm observations. Columns (1) and (3) replicate the results from column (5) of Table 2 and Table 3 respectively. In the columns (2) and (4), we check the robustness of the estimated heterogeneous effects of robots by additionally allowing for heterogeneous effects of the other technology and innovation variables. The log changes in ICT, R&D, and software and databases are interacted with the dummy variables for the quintiles of baseline TFP respectively markups (i.e., $Quin1$ to $Quin5$). The regression equations are estimated by OLS using overlapping five-year differences. See Table 2 for a detailed description of control variables. Standard errors clustered by country x industry in parentheses. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

Table A.3: Estimated production function coefficients. Using the robot density instead of the log robot stock.

		Production function coefficients			
Industry	Code	Labor	Materials	Capital	RTS
Food products, beverages, tobacco	10-12	0.24	0.67	0.10	1.01
Textiles, leather, wearing apparel	13-15	0.41	0.49	0.06	0.96
Wood and wood products	16	0.33	0.60	0.08	1.00
Paper and paper products	17-18	0.41	0.51	0.07	0.99
Other chemical products	19-20	0.29	0.62	0.10	1.01
Pharmaceuticals, cosmetics	21	0.39	0.57	0.03	0.99
Rubber and plastic products	22	0.24	0.65	0.07	0.97
Other non-metallic mineral products	23	0.35	0.56	0.10	1.02
Basic metals	24	0.33	0.62	0.05	1.00
Fabricated metals	25	0.42	0.46	0.10	0.98
Electronics	26-27	0.38	0.56	0.06	1.00
Industrial machinery	28	0.38	0.54	0.07	0.99
Motor vehicles	29	0.32	0.58	0.09	0.99
Other transport equipment	30	0.34	0.58	0.04	0.97

Note. These are the results of the production function estimation, assuming a Cobb-Douglas production technology, and including the (lagged) change in the robot density in the productivity process. The industries are classified according to ISIC Rev. 4. Returns to scale RTS. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, own calculations.

Table A.4: Estimated production function coefficients. Translog production technology.

		Production function coefficients							
Industry	Code	Labor		Materials		Capital		RTS	N
Food products, beverages, tobacco	10-12	0.24	(0.16)	0.67	(0.18)	0.10	(0.05)	1.01	101,270
Textiles, leather, wearing apparel	13-15	0.30	(0.14)	0.61	(0.22)	0.06	(0.04)	0.97	64,519
Wood and wood products	16	0.32	(0.16)	0.62	(0.17)	0.07	(0.02)	1.01	28,277
Paper and paper products	17-18	0.40	(0.17)	0.51	(0.18)	0.07	(0.03)	0.98	48,151
Other chemical products	19-20	0.32	(0.16)	0.61	(0.18)	0.09	(0.05)	1.02	37,468
Pharmaceuticals, cosmetics	21	0.35	(0.15)	0.59	(0.16)	0.05	(0.04)	1.00	7,311
Rubber and plastic products	22	0.30	(0.13)	0.60	(0.15)	0.08	(0.01)	0.99	45,956
Other non-metallic mineral products	23	0.33	(0.14)	0.60	(0.17)	0.09	(0.05)	1.02	40,235
Basic metals	24	0.33	(0.17)	0.62	(0.17)	0.05	(0.01)	1.00	20,934
Fabricated metals	25	0.44	(0.14)	0.46	(0.17)	0.09	(0.03)	0.99	147,458
Electronics	26-27	0.36	(0.17)	0.58	(0.18)	0.06	(0.03)	1.00	58,578
Industrial machinery	28	0.32	(0.16)	0.63	(0.16)	0.06	(0.02)	1.00	91,136
Motor vehicles	29	0.32	(0.14)	0.60	(0.17)	0.09	(0.05)	1.00	17,517
Other transport equipment	30	0.36	(0.21)	0.56	(0.21)	0.07	(0.03)	0.99	9,063

Note. These are the results of the production function estimation, assuming a translog production technology, and including the (lagged) log change in industrial robots in the productivity process. The production function coefficients represent averages over all firms in an industry, the corresponding standard deviations are given in parentheses. The industries are classified according to ISIC Rev. 4. Returns to scale RTS. Number of observations N. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, own calculations.

Table A.5: First stage results.

	△ ln(TFP)		△ ln(Markup)	
	IV, set A	IV, set B	IV, set A	IV, set B
	(1)	(2)	(3)	(4)
[A] F-Test on excluded instruments				
△ ln(Robots) x Quin1	8.649	17.875	9.219	22.399
x Quin2	8.652	14.428	9.103	28.069
x Quin3	8.519	16.568	7.910	19.138
x Quin4	8.198	15.038	8.496	18.284
x Quin5	8.174	14.318	9.831	15.218
[B] Kleibergen-Paap weak identification test				
	12.439	9.429	14.041	10.448
[C] Baseline specification				
C.1 F-Test on excluded instruments				
△ ln(Robots)	33.699	24.145	33.697	24.145
C.2 Kleibergen-Paap weak identification test				
	58.914	37.611	58.910	37.610

Note. Based on the IV estimations in the columns (7) and (8) of Table 4, this table presents the corresponding first stage results. Panel A shows the F-Statistics on the excluded instruments. Since there are five potentially endogenous variables, we estimate five first stage regressions for each model, and hence obtain the same number of F-Statistics. Panel B shows the Kleibergen-Paap rk Wald F-statistics in order to test for weak identification. In Panel C, we present the same test statistics for the baseline specification, i.e., for the model without allowing for heterogeneous effects of robots. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

Table A.6: Robustness checks for the effect on sales.

	Density	Ind. dummies	Not lagged	$\triangle_4$	$\triangle_3$	IV, set A	IV, set B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\triangle$ Robots x Quin1	-0.0034*	-0.0625***	-0.0478***	-0.0666***	-0.0702***	-0.0171	-0.0358
	(0.002)	(0.018)	(0.016)	(0.015)	(0.011)	(0.028)	(0.025)
x Quin2	0.0013	-0.0162	0.0026	-0.0110	-0.0137	0.0293	0.0117
	(0.002)	(0.012)	(0.016)	(0.015)	(0.013)	(0.026)	(0.023)
x Quin3	0.0042*	0.0016	0.0210	0.0043	-0.0025	0.0500**	0.0342
	(0.002)	(0.013)	(0.021)	(0.020)	(0.017)	(0.025)	(0.024)
x Quin4	0.0056**	0.0214	0.0347*	0.0214	0.0117	0.0587**	0.0452*
	(0.002)	(0.013)	(0.021)	(0.019)	(0.018)	(0.025)	(0.023)
x Quin5	0.0061**	0.0215	0.0319	0.0217	0.0129	0.0527*	0.0428
	(0.003)	(0.017)	(0.022)	(0.023)	(0.019)	(0.030)	(0.027)
N	110,727	110,710	114,140	171,570	228,313	110,710	110,710

Note. Based on N firm observations. This table presents robustness checks for the heterogeneous effects of robots on sales, based on the specification in column (5) of Table 5. The regression equations are estimated by OLS using overlapping differences. Column (1) uses the change in the robot density – the change in robots per thousand workers – instead of the log change in robots as the main variable of interest. In column (2), we add industry dummies to control for industry trends. Columns (3)–(5) check the robustness of the results with regard to timing issues, by not lagging the log change in robots (column 3), and by using four-year (column 4) and three-year (column 5) instead of five-year differences. Columns (6) and (7) present IV estimations where over-identified models are estimated using 2SLS. The industry-level robot stock in the sample countries is instrumented with robot installations in the US and the UK (set A), or in the US, the UK, Norway, Belgium, Portugal, and Austria (set B). Standard errors clustered by country x industry in parentheses. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

Table A.7: First stage results for the effect on sales.

	IV, set A	IV, set B
	(1)	(2)
[A] F-Test on excluded instruments		
△ ln(Robots) x Quin1	10.517	17.801
x Quin2	9.910	23.149
x Quin3	9.567	13.967
x Quin4	11.819	23.920
x Quin5	10.698	18.015
[B] Kleibergen-Paap weak identification test		
	13.181	11.241
[C] Baseline specification		
C.1 F-Test on excluded instruments		
△ ln(Robots)	33.699	24.145
C.2 Kleibergen-Paap weak identification test		
	58.914	37.611

Note. Based on the IV estimations in the columns (6) and (7) of Table A.6, this table presents the corresponding first stage results. Panel A shows the F-Statistics on the excluded instruments. Since there are five potentially endogenous variables, we estimate five first stage regressions for each model, and hence obtain the same number of F-Statistics. Panel B shows the Kleibergen-Paap rk Wald F-statistics in order to test for weak identification. In Panel C, we present the same test statistics for the baseline specification, i.e., for the model without allowing for heterogeneous effects of robots. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

Table A.8: First stage results for the effect on the labor share.

	Unweighted		Weighted by firm sales	
	(1)	(2)	(3)	(4)
	IV, set A	IV, set B	IV, set A	IV, set B
F-Statistic on excluded instruments	53.404	20.312	51.014	20.307
Kleibergen-Paap rk Wald F-statistic	104.093	39.585	100.588	38.802

Note. Based on the IV estimations in Panel B of Table 6, this table presents the corresponding first stage results. We show the F-Statistics on the excluded instruments and the Kleibergen-Paap rk Wald F-statistics in order to test for weak identification. Levels of significance: *** 1%, ** 5%, * 10%. Sources: Amadeus, IFR, OECD Stan, Eurostat SBS, EU KLEMS, Comtrade, own calculations.

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