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Original article

Automation and productivity—a cross-country, cross-industry comparison

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Abstract

We investigate the effects of automation on total factor productivity (TFP). Using industry-level panel data for nine countries, we find that more intensive use of industrial robots has a significantly positive effect on TFP. Specifically, an increase of one standard deviation in the robot intensity is associated with more than 6% higher TFP. Moreover, we find that the robot intensity increases with Chinese import competition and that automation is associated with higher wages and unchanged or higher employment.

JEL classification: C23, J24, O33, O47

1. Introduction

The manufacturing sector has been under pressure in most developed countries. The rise of and competition from low-wage countries has led many manufacturing firms in the developed world to either closedown or offshore parts of the manufacturing process. This has led to a visible shift in manufacturing activity, as shown in Figure 1. In 1995, the developing countries produced around 24% of all manufacturing goods in the world. In 2007, this number was up by 13% points to 37%, and in 2011, the developing countries were responsible for almost half of total world production (47%).

In the same period, the employment share of the manufacturing sector in the developed world has declined from around 16% in 1995 to about 12% in 2011 (Figure 2). Conversely, the employment share of the manufacturing sector in the developing countries has increased from around 11% in 2003 to 13% in 2011 and has exceeded the share in the developed countries since 2009.

It has been argued that the above development might in the longer run jeopardize continued welfare improvements in the developed part of the world. The current downsizing of the manufacturing sector is, therefore, a cause for concern among policy makers in these countries. Therefore, they have been looking for clever ways to bring back the manufacturing production and, especially, the manufacturing jobs that are expected to be lost as a consequence of this development.

It seems natural to ask whether robots have a role to play in this process. Can they create the growth in productivity that is needed to keep a manufacturing sector in the developed world? In recent years, the costs of automation

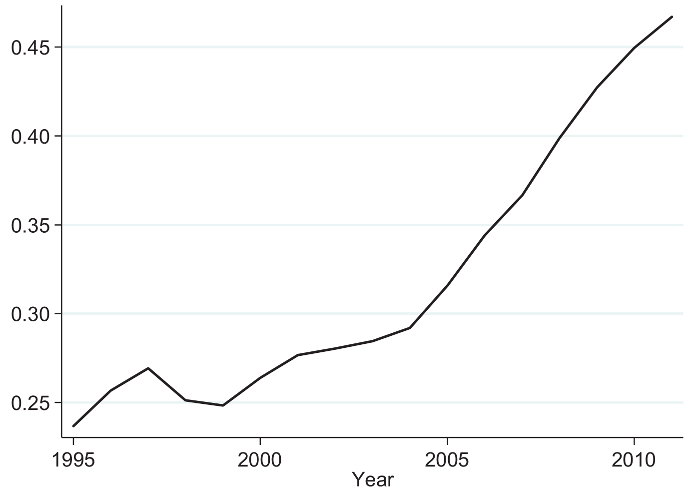

Figure 1. Manufacturing production in developing countries as a share of total world production. *Note*: The data source is the World Input–Output Database (WIOD) in current prices. The data covers 40 countries: 27 EU countries (Austria, Germany, the Netherlands, Belgium, Greece, Poland, Bulgaria, Hungary, Portugal, Cyprus, Ireland, Romania, the Czech Republic, Italy, the Slovak Republic, Denmark, Latvia, Slovenia, Estonia, Lithuania, Spain, Finland, Luxembourg, Sweden, France, Malta, and the UK) and 13 other major countries (the United States, Canada, India, Japan, China, South Korea, Australia, Taiwan, Turkey, Indonesia, Russia, Brazil, and Mexico). It covers 35 industries, including 14 manufacturing industries. The 40 countries cover more than 85% of world GDP. To cover the remaining countries in the world, WIOD includes a region called the Rest of the World (RoW) that proxies for all remaining countries in the world. WIOD covers the period from 1995 to 2011 and is measured in US dollars. For more information: see www.wiod.org and Timmer *et al.* (2015). We have divided the countries into developed and developing countries according to the World Bank classification. The developing countries consist of Bulgaria, Romania, Brazil, Mexico, China, South Korea, India, Indonesia, Turkey, and RoW. The Figures shows total value-added generated in manufacturing in the developing countries as a share of total value-added generated in manufacturing in the world.

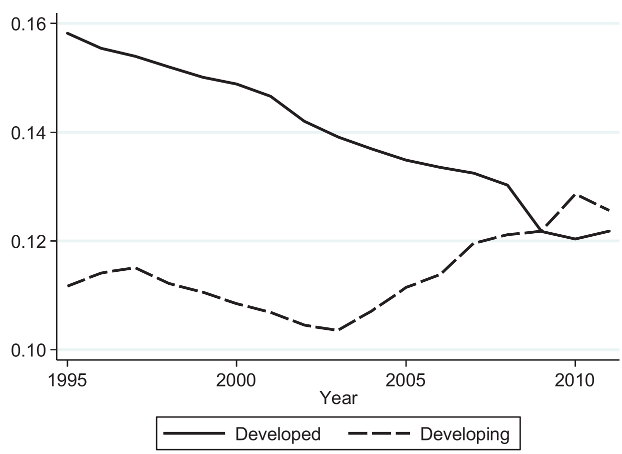

Figure 2. Employment shares in manufacturing, developed and developing countries. *Note*: The data source is the World Input–Output Database, which covers 40 countries and 35 industries (see note to Figure 1). We have divided the countries into developed and developing according to the World Bank classification. We measure the employment share in manufacturing as the number of persons engaged in the manufacturing sector relative to the total number of persons engaged.

have decreased and machines have improved in terms of their ability to handle more advanced tasks. Moreover, robots have become easier to program, and therefore, to use in different types of manufacturing industries. Furthermore, innovation is vital to competitiveness in the global economy, and the development and use of new technology, including automation in manufacturing, Industry 4.0 (which refers to the coordinated use of robots),

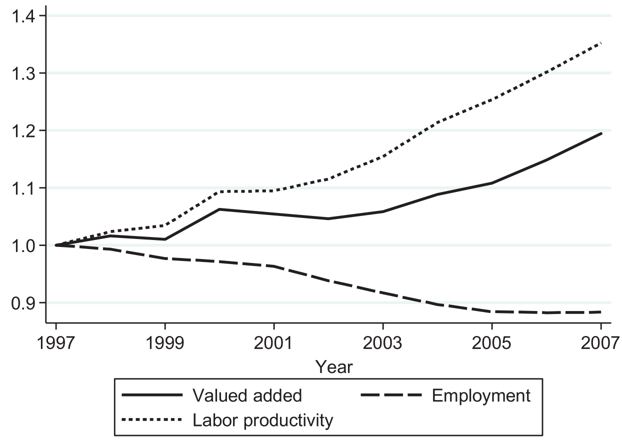

Figure 3. Aggregate labor productivity in manufacturing, developed countries. *Note*: The data source is the EUKLEMS Database. Value-added is total PPP-corrected valued added in the 14 developed countries included in our study: Austria, Belgium, the Czech Republic, Denmark, Spain, Finland, France, Germany, Hungary, Italy, Japan, the Netherlands, Sweden, and the UK. Employment is the total number of person engaged in these countries. Labor productivity is value-added divided by employment. All three variables are measured relative to the level in 1997.

artificial intelligence, sensors, and other information technology (IT)-based technologies in manufacturing are at the forefront of discussions and important topics on the policy agenda. The business press has also emphasized the importance of automation for some time, and it is in general expected that technological innovations will play an important role for productivity and growth (Council of Economic Advisers, 2016).

Thus, there seems to be great belief in the potential of robots for providing productivity improvements—especially in developed countries where labor costs are high. Industrial robots are certainly also growing in numbers. According to the International Federation of Robotics (2011), the number of operational industrial robots in the world increased by 4% per year from 2004 to 2009, and most of this increase took place in developed countries. Despite these developments, we still know surprisingly little about the actual productivity and employment effects of industrial robots.

Obviously, labor productivity must be expected to increase from automation, because industrial robots can directly substitute for some unskilled workers. An early study by Fleck (1984) has thus estimated that one robot can replace two to six workers on average. A more interesting question is whether robots can also increase total factor productivity (TFP) by, for example, increasing the quantity and quality of the products, decrease waste and/or expanding the product portfolio, and how that affects employment.

Figure 3 shows the development in aggregate labor productivity (i.e. value-added per worker) in the manufacturing sector across the 14 developed countries that we use in our empirical analysis. It is seen that labor productivity has increased by more than 35% over the 10-year period from 1997 to 2007. This is equivalent to an annual increase of 3.1%. It is also seen that value-added has been growing, while employment has been falling, which can be explained by both capital deepening and higher TFP.

In this article, we shall investigate whether an increase in TFP is related to investments in industrial robots. We also study the labor market effects from increasing automation, and the drivers of investments in industrial robots. Do industries in the developed world invest in industrial robots as a consequence of increasing competition from low-wage countries?

The dataset that we use comes from the International Federation of Robotics (IFR) that collects these data for a number of different industries and countries. We thus have data for 10 manufacturing industries in nine countries for the period 2004–2007. We use these data to estimate a production function at the industry level. In doing this, we distinguish explicitly between information and communication technology (ICT) capital and non-ICT capital, thereby follow the approach taken in the literature on ICT capital and productivity (the meta-study by Stiroh, 2005). To test the importance of robots for TFP in the industry, we include a robot-intensity index, calculated as the number of industrial robots relative to the non-ICT capital stock in the industry.

A potential drawback to using the quantity of industrial robots as an explanatory variable is that quality changes and differences are not accounted for. If the quality of industrial robots increases over time, the quantity of industrial robots will put too little weight on later vintages of robots and too much weight on early vintages. This is especially problematic if quality increases are substantial. There are many indications of quality increases over vintages of robots: In 1975, an average robot had five axes, a capacity of 6 kg and a reach of 1 m. These numbers had increased to 21 axes, a capacity of more than 120 kg and a reach of 2 m in 1995 and to 32 axes, a capacity of more than 1000 kg and a reach of at least 3 m in 2015 (Tilley, 2017). Similarly, if there are differences across industries or countries in the quality of robots used, these are not accounted for when using the number of robots as the measure of automation at the industry level.

In order to deal with this, we perform two sets of regressions. First, we estimate level regressions using the quantity of industrial robots as an explanatory variable. This analysis does not control for differences in robot quality across industries and over time—which may, therefore, contaminate the empirical results. Second, we estimate fixed-effects and first-difference regressions that rely on the changes in the quantity of robots within an industry in a country over time to identify the parameters of interest. These estimations thus eliminate the effects of systematic time-invariant differences in the quality of the robot stock across industries and countries, for example, as a result of industry and country-specific robot types. To handle the issue that the quality of robots acquired may change over time, as a result of different vintages, we focus on a short period of time for which quality changes of robots are likely to be relatively modest. To the best of our knowledge, this article is the first to study the relationship between automation and productivity when quality differences and changes are accounted for.

The main result of the article is that automation of the production process has a positive and significant effect on productivity. The magnitude of the effect is such that an increase in the robot-intensity index by one standard deviation is associated with an increase in TFP of more than 6.5%. This result is remarkably robust to the use of different estimation methods and alternative samples.

Still, we are careful not to claim causality. Although the result survives when we control for unobserved productivity differences across industries and countries using either a fixed-effects or first-difference estimation, it might still reflect unobserved shocks that affect both productivity and the robot intensity. To get closer to a causal interpretation, we instrument the robot-intensity index using lagged changes in the index, which is a commonly used approach in the literature to deal with potential endogeneity of the explanatory variable (Stiroh, 2005). Our findings provide strong support for a causal relationship between the robot intensity and productivity.

Another important result is that the robot-intensity index increases more within industries that are affected more by Chinese import competition. This suggests that manufacturing industries in the developed countries react to increasing competition by adopting robot technology that contributes to higher TFP.

Finally, we find that an increase in automation is associated with higher average wages and unchanged or higher employment at the industry level. Combined with the positive productivity effect of industrial robots, this at least indicates that increased automation may be a way to bring back manufacturing production in the developed countries; and that this need not come at the expense of labor.

The rest of the article is structured as follows. In the next section, we present a short literature review. In Section 3, the theoretical and empirical framework is presented in detail. In Section 4, we present the data and descriptive statistics, whereas the empirical analysis is contained in Sections 5 and 6. Section 7 concludes.

2. Literature review

There has been considerable focus on technology as a source of higher productivity growth in manufacturing. However, the typical measure of technology used in empirical studies is not a robot-based measure. Instead, technology is often measured as expenditures on R&D, the number of patents, and/or the amount of ICT capital. Alternatively, it is measured through survey questions about innovation activities (Hall, 2011; Hall *et al.*, 2010).

During the past two decades, many studies of ICT capital have been carried out using both aggregate data and firm-level data (Stiroh, 2002; Jorgenson *et al.*, 2008; van Ark *et al.*, 2008; Draca *et al.*, 2009; Bloom *et al.*, 2012). The purpose of this literature has been (i) to estimate the contribution of ICT (or IT) capital to output growth and (ii) to determine whether ICT (or IT) capital is associated with excess returns. The approach taken has been to split total capital into ICT capital and non-ICT capital and to estimate a production function that includes both types of capital in addition to labor and intermediate inputs. If the estimated output elasticity of ICT capital is found to exceed its factor share, this is interpreted as evidence of excess returns, and hence that ICT capital contributes to TFP growth. We also follow this approach below in the applied estimation framework. Early studies found that ICT capital had no impact on TFP. This might have been due to noisy data and poor estimation methods. A recent study by Cardona *et al.* (2013), which summarizes the findings of more recent empirical studies, concludes that ICT capital does indeed play an important role in the productivity statistics, but that the evidence is most pronounced for the United States, while the evidence for European countries is more ambiguous.

However, these "traditional" technology measures affect a number of activities outside the production process itself. R&D spending and the number of patents are thus relevant input and output measures, respectively, of knowledge production. ICT capital includes computer hardware, computer software, and telecommunication equipment, and much (or most) of this is used in activities such as distribution, accounting, administration, knowledge production, sales, and marketing. Therefore, these measures are not particularly informative about the automation level of the production process itself and hence not well suited for analyzing the role played by industrial robots.

The only micro-level papers that address automation and firm performance are Bartel *et al.* (2007, 2009). Bartel *et al.* (2007) find that the use of more advanced computerized numerically controlled machines in the valve-manufacturing industry in the United States raises productivity by shortening setup time, production time, and inspection time. Bartel *et al.* (2009) perform the same analysis for the UK and find similar results.

Another strand of literature that considers the relationship between productivity and new technology is the endogenous-growth literature. Romer (1990) present a variety-based endogenous-growth model where growth is driven by an expanding set of complementary intermediate inputs. Steady-state growth can be positive and depends on long-run factor allocation. The growth generating sector is an R&D sector where production of new ideas takes place. Jones and Williams (1998) link the theoretical models of endogenous-growth literature to the results in the empirical literature on productivity. Specifically, they study the analytical relationship between the true social rate of return to R&D and the coefficient estimates from regressions of TFP growth on R&D investments. The authors conclude: "Despite the methodological limitations of the productivity literature—[.]—we show that the estimates in this literature represent *lower* bounds on the social rate of return to R&D", thereby linking these two strands of literature. The approach that we follow in the present paper is that from the productivity literature.

Only a few papers so far have used data from IFR on the number of industrial robots at the industry level. Acemoglu and Restrepo (2018) analyze long-run effects of the increased use of industrial robot in the US labor market. A robust negative effect of robots on employment and wages is found across US commuting zones between 1990 and 2007: one more robot per thousand workers reduces the employment to population ratio by about 0.2% points and wages by 0.37%. Graetz and Michaels (2018) study the impact of robot use on labor productivity growth over the period 1993 to 2007 using long differences. Their findings suggest that increased robot use contributed around 0.36% points to annual labor productivity growth, while at the same time raising TFP and lowering output prices. Neither of these studies take into account that the quality of industrial robots may have changed over time (from 1990 to 2007). As explained above, this may distort their measure of the robot stock, which may in turn bias the obtained results. This is, especially, relevant for the productivity study of Graetz and Michaels (2018).

3. Theoretical and empirical framework

We extend the production function used in the literature on ICT capital and productivity—as discussed above—to account for the effects of industrial robots. Specifically, we want to separate the effects of industrial robots from any effects of ICT capital. Industrial robots are part of the non-ICT capital measure, but the data does not allow us to split up non-ICT capital into industrial robots and other types of non-ICT capital. Instead, we include a robot-intensity index that provides a measure of the number of industrial robots relative to the amount of total non-ICT capital as an extra regressor. Including such an index in addition to the overall measure of non-ICT capital, is in line with the approach taken in the literature on human capital and growth, where both a headcount of labor and a quality index of labor are included (see below). It should be emphasized that the index measures the quality of non-ICT capital by introducing a measure of capital composition. It does not account for quality changes in robots over time or across industries and countries as we discussed in the Section 1. If the robot-intensity index is found to have a separate positive effect, we take this as evidence that industrial robots have an additional/excess effect on value-added (and hence a TFP effect) compared to other types of non-ICT capital.

The logic in our empirical specification is based on the following production function:

$$Y_{ijt} = A\left(C_{ijt}\right)^{\alpha}\left(Q_{ijt}\right)^{\beta}\left(H_{ijt}\right)^{\gamma}, \tag{1}$$

where Y denotes value-added in industry i of country j in year t. C is input of ICT capital, Q is input of non-ICT capital, and H is labor input. Following common practice, we assume that this relationship can be approximated by a Cobb-Douglas production function. Importantly, input of non-ICT capital and labor input both have a quality and a quantity dimension, such that $Q = qK$ and $H = hL$, where K denotes the quantity of non-ICT capital, and L denotes the number of hours worked, while h is (average) human capital per worker and q is (average) quality of non-ICT capital.

The above production function can be re-written in log-form as:

$$y_{ijt} = a_{ijt} + \alpha c_{ijt} + \beta log\left(q_{ijt}\right) + \beta k_{ijt} + \gamma log\left(h_{ijt}\right) + \gamma l_{ijt}, \tag{2}$$

where y, a, c, k, and l are the logs of Y, A, C, K, and L, respectively.

To arrive at our empirical specification, we need to define measures of q and h. For q, we want to take the intensity of industrial robots into account. Therefore, we use the following measure of q:

$$q_{ijt} = e^{\xi RI_{ijt}}, \tag{3}$$

where RI is an index for the stock of industrial robots relative to the total non-ICT capital stock, and ξ captures the effect of the index on the quality of the non-ICT capital stock. Specifically, the robot-intensity index is constructed as follows:

$$RI_{ijt} = \frac{R_{ijt}}{K_{ijt}}, \tag{4}$$

where R is the quantity of industrial robots in industry i of country j in year t. Similar intensity indices have been used in related strands of literature, for example, by Feenstra and Hanson (1999), who apply outsourcing intensities in an analysis of the causes of increasing wage inequality, and by Lichtenberg and Griliches (1984), who use R&D-intensities in their study of productivity growth. The robot-intensity index will be discussed in more detail in the next section after the data have been introduced.

When it comes to h, we simply assume that it is a constant in our baseline model implying that the term containing h becomes part of the constant term in the regression model. However, in one of our robustness analyses, we measure h following the approach in the macro models of human capital and growth applied by, for example, Hall and Jones (1999) and Klenow and Rodriguez-Clare (1997). They assume a human-capital function of the following form:

$$h_{ijt} = e^{\lambda S_{ijt}}, \tag{5}$$

where S is the share of skilled workers among all workers in industry i of country j in year t, and λ captures the effect of the share of skilled workers on the quality of labor. This approach follows Gemmell (1996), who recommends using shares of workers with different skill levels (defined by educational attainment) as a measure of labor quality rather than standard measures such as years of schooling or enrollment rates, as the latter measures will tend to conflate the human capital stock and the accumulation of human capital in growth regressions.

Given the above assumptions, the production function used for estimation purposes can be expressed as:

$$y_{ijt} = a_{ijt} + \alpha c_{ijt} + \delta RI_{ijt} + \beta k_{ijt} + \eta S_{ijt} + \gamma l_{ijt}, \tag{6}$$

where $\delta = \beta\xi$ is the marginal return to the robot-intensity index, RI, and $\eta = \gamma\lambda$ is the marginal return to S, the share of skilled workers. Note that if there are constant returns to scale in the production, the sum of the three elasticities, α, β, and γ, equals one.

The parameter of main interest in this study is δ. If industrial robots have an extra effect compared to other types of non-ICT capital, industries with higher (or faster growing) RI are expected to have higher (or faster growing) productivity, that is, δ should be positive. This is the hypothesis that we investigate in the following.

We refer to a positive value of δ as an effect of industrial robots on TFP. Even though the effect works through the composition of non-ICT capital, we interpret this as an effect working through TFP since such effects are normally part of the unexplained component in productivity estimations. A higher effect of industrial robots compared to other types of non-ICT capital could stem from the fact that they not only substitute for other types of non-ICT capital (and labor) but that they can improve the quality of the products produced and help expand the product portfolio. Thus, many devices, designs, varieties, and quality improvements could not be produced without the help of industrial robots.[1]

When estimating (6), we need to put some restrictions on a_{ijt} in order to be able to identify δ and to obtain consistent estimates of the involved parameters. In the simplest case where a_{ijt} can be expressed as the sum of a constant, a_0, and a random error that is uncorrelated with the regressors, ordinary least squares (OLS) estimation of (6) will result in consistent estimators of α, β, γ, η, and δ.

However, if there are TFP differences between countries or between industries that are correlated with (but not caused by) the robot intensity (or the other regressors), the OLS estimators will become inconsistent. Therefore, we include country and industry fixed effects to allow a_{ijt} to vary systematically across countries and industries due to, for example, different production technologies. As discussed in Section 1, the fixed effects will also control for systematic differences in the quality of the robot stock across industries and countries not captured by our robot-intensity index. Furthermore, we include year fixed effects to allow a_{ijt} to vary across time to capture productivity trends that might be correlated with the development in the number of robots used.

As discussed above, we also include a measure of human capital into our production function. As an increasing use of industrial robots requires a workforce that is more skilled in order to adopt and use the robots efficiently, and because a more skilled workforce might in itself influence productivity positively, it is important to control for the development in human capital in the regressions.

In sum, we end up with the following empirical model:

$$y_{ijt} = \alpha c_{ijt} + \beta k_{ijt} + \gamma l_{ijt} + \delta RI_{ijt} + \eta S_{ijt} + a_0 + b_i + d_j + e_t + \epsilon_{ijt}, \tag{7}$$

where b_i, d_j, and e_t are the industry, country, and year fixed effects, respectively. Although this specification is likely to capture most of the TFP differences that may be correlated with (but not caused by) the robot intensity, there is still a risk that some differences may remain at the industry-country level. To deal with this possibility, we also estimate the model in (6) using industry $\times$ country fixed effects, and we also estimate the model in first differences. Both of these methods eliminate the effects of time-invariant factors that are specific to a given industry in a given country.

Still, if there are time-varying shocks to a_{ijt} that also affect the robot-intensity index (which would be the case if productivity shocks drive the investments in industrial robots), this may render our robot-intensity index in (6) endogenous, and hence cause the OLS, fixed-effects and first-difference estimators of δ to be inconsistent. To check for this, we instrument the level of the robot intensity in a given industry-country cell using lagged changes in the variable. This is a standard approach used in the literature (Stiroh, 2005).

4. Data and descriptive statistics

Three different data sources are used to construct the dataset that we use in the subsequent analyses. First, input and output data are taken from the EUKLEMS database November 2009 release, which contains industry-level measures of output, inputs, productivity, and worker quality for 25 European countries, Japan, and the United States for the period 1970–2007. O'Mahony and Timmer (2009) provide a description of the EUKLEMS data. Second, we use data on industrial robots from the International Federation of Robotics (2011) to develop our industry-level measure of the robot intensity. Third, we use the World Input–Output Database (WIOD) to construct the measures of import competition. See Timmer *et al.* (2015) for a description of the WIOD data.

IFR uses the definition of a "manipulating industrial robot" given by the ISO 8373 standard from the International Organization for Standardization. This standard defines an industrial robot as: *An automatically*

1 A positive effect of the robot-intensity index may also reflect that industrial robots (at their current level) are associated with higher marginal returns than other types of non-ICT capital, but due to, for example, adjustment costs, there is still "underinvestment" in robots. In any case, finding a positive effect of the robot-intensity index will indicate that further investments in industrial robots will increase labor productivity for a given level of capital, which is equivalent to a TFP effect.

controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications (International Federation of Robotics, 2011: 6). IFR collects their data from the producers of robots. They provide data both on shipments/sales of robots to industries in different countries and on the operating stock of robots in different countries. In calculating the operating stock, it is assumed that the average operating service life of an industrial robot is 12 years. In other words, the database uses a "one-hose shay" depreciation method.[2]

Even though we refer to the quantity of industrial robots as a stock variable, it is not a capital stock in the usual sense of the word, as the measure is not quality adjusted. A specific robot type may thus obtain higher capacity over time; cf. the example in the Section 1. Robots also become more and more integrated over time such that a single robot may now handle production tasks that were previously performed by a number of different robots. In this case, the number of robots will underestimate the actual stock and degree of automation in sectors and countries where investments in recent years have been relatively high, and it will overestimate the stock in sectors and countries where investments in recent years have been low. Furthermore, the large variation in the complexity of different types of industrial robots is not taken into account when using the number of industrial robots instead of the amount of robot capital as a measure of automation.

IFR has developed two price indices for the period 1990 to 2005; one is quality adjusted and one is not. The difference between the two price indices measures the development in robot quality from 1990 to 2005. To the best of our knowledge, this is the only index that exists for the quality of industrial robots. It is difficult to assess how precise the index is. However, we can at least use it as an approximation—to assess whether quality changes in industrial robots potentially is an important issue that we have to consider. [3]

In Figure 4, we present the two price indices in panel a, and we include the deduced quality index in panel b. It is seen that the quality of robots increases markedly and, for example, doubles during the period 1993–2005. Taken at face value this implies that one 2005-vintage industrial robot is as productive as two 1993-vintage industrial robots. Moreover, the average annual improvement in quality is 6.2% for the full period and 2.3% for the 5 years up to 2005. In other words, according to this index, quality changes are indeed something that should be considered in an analysis of industrial robots, and we, therefore, spend considerable effort dealing with this potential problem in the empirical analyses below.

From the EUKLEMS database, we get data on value-added, ICT capital, non-ICT capital, hours worked by persons engaged (labor input), and the share of skilled workers at the industry level. Capital inputs are measured by the total capital service flows, which are obtained by aggregating over the different asset types assuming a translog function of the services of the individual capital types (O'Mahony and Timmer, 2009). Industrial robots do not constitute a separate type of capital in the EUKLEMS, which is why we apply the robot index described above as our measure of automation. We use PPP (purchasing power parity) corrected variables since the levels regressions require that cross-country variables are measured in comparable units (Inklaar and Timmer, 2008 for a description of these variables). Given that the period analyzed is 2004–2007, the results are not influenced by the large cyclical fluctuations financial crisis in the following years.

2 A model of depreciation, in which a robot delivers the same services from purchase until failure, with zero scrap value. Also known as the light bulb model of depreciation.

3 IFR performs a rough quality adjustment of the robot price index (International Federation of Robotics, 2007: Annex C). The applied method is based on production-cost mark-up and uses the following assumptions: (i) the robot is composed of three parts: a control unit; a mechanical unit whose characteristics are changed over time (the arm, drives, sensors, etc.); and a mechanical unit with fixed characteristics (e.g. casings and certain steel structures). (ii) Cost shares distribution: control unit (20%); mechanical unit with changing characteristics (40%); mechanical unit with fixed characteristics (40%). (iii) the characteristics of the control unit are the same as those of computers. The cost index for the control unit is therefore approximated by a mark-up using the US producer price indices (PPI) for computers. (iv) Measurements of improvements in the mechanical characteristics are limited to: total handling capacity in kg (20%); Repetition accuracy in mm (30%); total aggregated speed of all six axes in degrees per second (B/s) (30%); and total maximum reach in mm (20%). It is assumed that costs are directly proportional to the weighted increase in mechanical characteristics. Based on the above assumptions, the quality-adjusted prices are calculated to express what robots would cost, given that they were produced with a base-year level of the above characteristics.

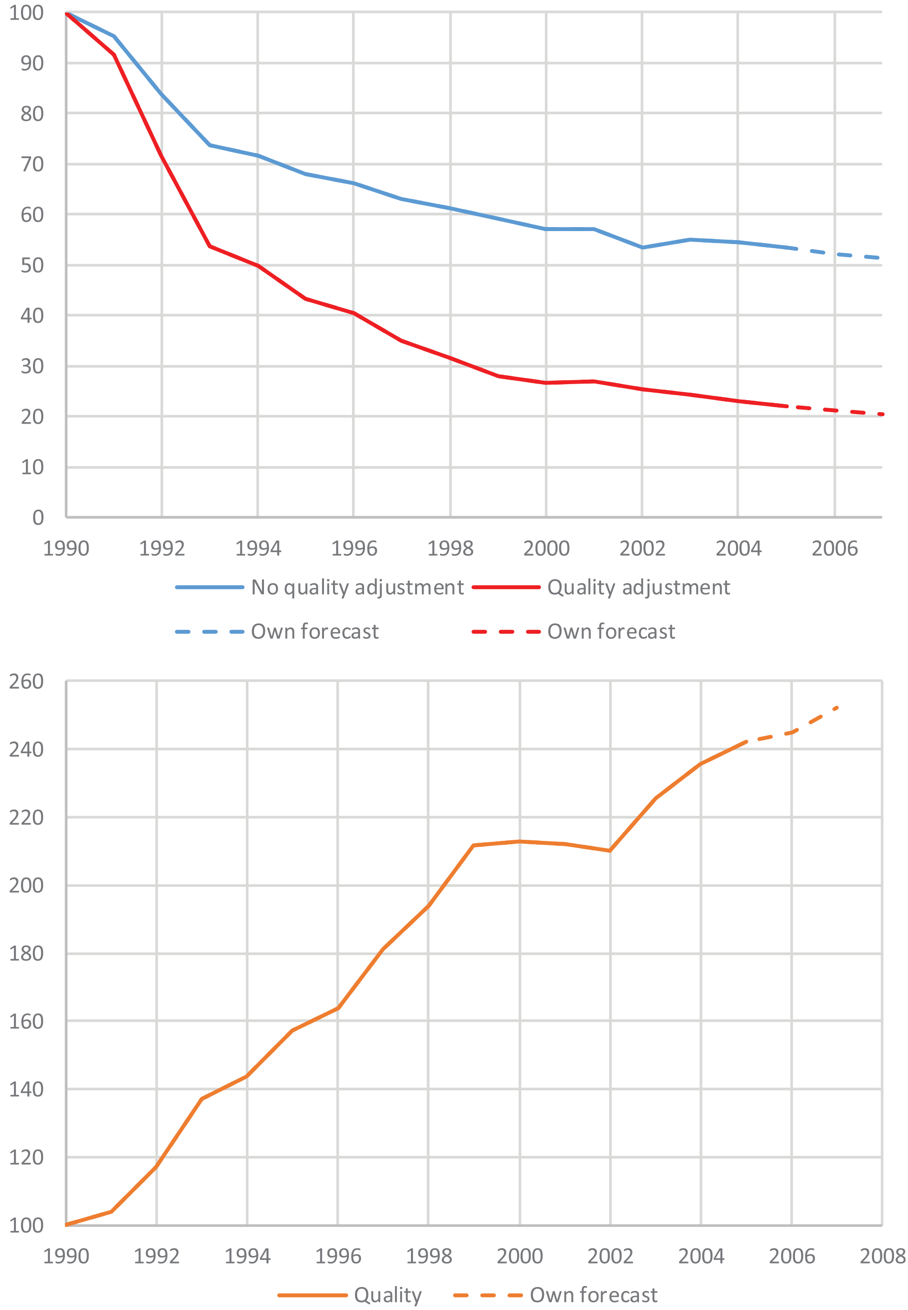

Figure 4. Price index of industrial robots for international comparison (based on 1990 USD conversion rate). (a) Price index w and w/o quality adjustment. (b) Quality index of industrial robots.

By merging the IFR data on the stock of industrial robots with the EUKLEMS data, we obtain a dataset covering nine countries and 10 manufacturing industries for the period 2004–2007.[4] Even though the IFR data also includes

4 The countries in the study are Japan, Germany, UK, France, Italy, Spain, Sweden, Finland, and Denmark. The industries are (ISIC rev. 4 industry codes in parentheses): food, beverages, and tobacco (10–12); textiles, leather, and wearing

Table 1. Total robot intensity across countries, 2004 and 2007

Country	2004	2007
Denmark	0.39	0.63
Spain	0.52	0.62
Finland	0.33	0.40
France	0.55	0.66
Germany	1.60	1.80
Italy	0.72	0.80
Japan	0.98	0.85
Sweden	0.32	0.38
UK	0.25	0.30

Note: The robot intensity in a country is measured as the total number of robots per million Euros non-ICT capital (measured in 1997 German prices) across the 10 industries in the manufacturing sector (see Table 2 for a list of these).

Source: International Federation of Robotics (2011).

Table 2. Total robot intensity across industries, 2004 and 2007

Industry	2004	2007
Food, beverages, and tobacco	0.13	0.17
Textiles, leather, and wearing apparel	0.05	0.05
Wood and products of wood and cork	0.61	0.59
Paper, printing, and publishing	0.04	0.04
Chemical, rubber, plastic, and fuel	0.48	0.56
Glass, ceramics, stone, and mineral products	0.18	0.20
Metal and machinery	0.46	0.49
Electrical and optical equipment	0.93	0.69
Motor vehicles and other transport equipment	3.03	3.09
Other manufacturing products	3.57	2.67

Note: The robot intensity of an industry is measured as the total number of robots per million Euros non-ICT capital (measured in 1997 German prices) across the nine countries in the sample (see Table 1 for a list of these).

Source: International Federation of Robotics (2011).

data for sectors outside manufacturing, we disregard these as we want to focus specifically on the manufacturing sector. Furthermore, we have information on the shipment of industrial robots to an additional five countries.[5] These additional countries are low-intensive users of industrial robots, implying that the shipments can be used as proxies for the changes in their stocks of robots (by ignoring any depreciation of existing robots). Consequently, these countries will be included in a robustness analysis of the main results.

The robot intensity is measured as the number of industrial robots per million Euros non-ICT capital (measured in 1997 German prices using PPPs from the EUKLEMS database). Table 1 shows the overall robot intensity in the manufacturing sector for the nine countries in our sample in 2004 and 2007. As can be seen, the variation across countries is large. Germany is by far the most robot-intensive country, whereas the UK is the least robot-intensive country.

In all countries, except Japan, the robot intensity increased between 2004 and 2007. This reflects that the total number of industrial robots in the nine countries in Table 1 increased from around 600,000 in 2004 to around 630,000 in 2007; an increase of around 6%. The largest relative increases are found in countries with a relatively

apparel (13–15); wood and products of wood and cork (16); paper, printing, and publishing (17–18); chemical, rubber, plastic, and fuel (19–22); glass, ceramics, stone, mineral products n.e.c. (23); metal and machinery (24, 25, 28); electrical and optical equipment (26, 27); motor vehicles, trailers, semi-trailers, and other transport equipment (29, 30); and other manufacturing products (31, 32).

5 These countries are Austria, Belgium, the Netherlands, the Czech Republic, and Hungary.

Table 3. Summary statistics

	2004	Standard deviation	2007	Standard deviation	Min	Max
Value-added per person engaged (*Y*)	42.47	28.78	47.67	32.26	12.52	181.71
Persons engaged (*L*)	564.41	666.87	548.12	653.33	14.65	3411.17
Capital per person engaged	16.18	17.17	17.27	18.09	1.41	105.12
Non-ICT capital per person engaged (*K*)	13.28	15.34	13.74	15.82	0.88	97.08
ICT capital per person engaged (*C*)	2.89	2.61	3.53	3.28	0.19	14.77
Robot intensity (RI)	0.92	2.18	0.94	1.93	0	13.79
Industrial robots	6707	19,122	7097	20,406	0	137,310
Number of observations	89		89			

Note: Persons engaged are measured in millions hours worked, and value-added and capital are measured in millions of Euros using 1997 German prices. The robot intensity is measured as the total number of robots per million 1997 GER-EURO-PPP non-ICT capital. The industry "Other manufacturing products" is excluded for Sweden because values for non-ICT capital are not available. 2007 values for Japan are missing and replaced by 2006 values, except in the case of industrial robots.

Source: International Federation of Robotics (2011) and EUKLEMS.

low initial number of robots, such as Denmark, where the number of robots per million Euros non-ICT capital (1997 German prices) increased by 0.24; an increase of more than 60%. The falling robot intensity in Japan is due to an increase in non-ICT capital that exceeded the increase in industrial robots between 2004 and 2007. Note also that Japan holds more than half of the total number of industrial robots in the nine countries.

The robot intensity also varies considerably across industries as shown in Table 2, which presents the total number of industrial robots per million Euros non-ICT capital (1997 German prices) across the nine countries for each of the 10 manufacturing industries. *Motor vehicles and other transport equipment* and *other manufacturing products* are by far the most robot-intensive industries. The intensive use of robots within *Motor vehicles and other transport equipment* partly explains Germany's overall dominating role in the use of industrial robots. The least robot-intensive industry in both 2004 and 2007 was *paper, printing, and publishing*.

Note that the development in the robot intensity between 2004 and 2007 also varies across industries. In three out of 10 industries, the robot intensity actually decreased between 2004 and 2007, and these industries were relatively robot intensive, to begin with. *Electrical and optical equipment* thus experienced both a fall in the number of industrial robots and an increase in non-ICT capital. In Section 6.1, we investigate one potential explanation behind the different observed changes in the robot intensity between 2004 and 2007: the extent to which industries are exposed to import competition from China.

In sum, Tables 1 and 2 display considerable variation across countries and industries in the use of robots. A closer examination of the data reveals that the two industries with the largest variation across countries in 2007 are *Wood and products of wood and cork* and *motor vehicles and other transport equipment*. In the former industry, a value of 0.11 is observed for France, while Germany has a value of 4.29. In the latter industry, Sweden has a value of 1.09 and Italy has a value of 9.56. Similarly, the industry with the least variation across countries in 2007 is *Glass, ceramics, stone, and mineral products*, where Japan has the lowest value (0.10) and Germany the highest (0.57).

The considerable variation across countries and industries in the use of robots can be caused by many different factors. Cross-country variation in wages and in the prices of industrial robots may be part of the explanation for the country differences, but the industry structure of a country also affects its overall robot intensity. The fact that Japan has one of the highest numbers of industrial robots is not surprising as 47% of its manufacturing sales are concentrated within *Motor vehicles and other transport equipment* and *electrical and optical equipment*, which are among the most robot-intensive industries.

Across industries, differences in the supply of industrial automation solutions and different experience with automation as well as variation in production strategies also play a role. The number of industrial robots will thus depend on whether an industry is dominated by firms that produce customized products or firms that have mass production, as the potential for automation is much higher in the latter case.

In Table 3, we present summary statistics for the dependent and explanatory variables used in the empirical analyses below. Note that, on average, the amount of non-ICT capital in an industry is approximately four times larger than the amount of ICT capital, although ICT capital is becoming still more important. The average number of industrial robots in an industry is approximately 7000, but as shown in Tables 1 and 2, the variation is considerable.

5. Empirical results

In this section, we present the estimation results for our model in (7). Section 5.1 contains our baseline results, which are based on (pooled) OLS and fixed-effects regressions of the model in (7), and where we treat human capital as a constant. Section 5.2 presents estimates of the model using alternative estimation methods. First, the model is estimated in first differences which enable us to expand the number of countries to 14, as discussed in Section 4. Second, to check robustness and the importance of outliers, median, and weighted-least-squares (WLS) regressions are also used. Section 5.3 contains estimates of the full model where we include a measure for human capital. Finally, Section 5.4 contains IV results.

In all regressions, we use a normalized value of the robot-intensity index. Specifically, we divide all industry-country-year observations by the observation with the highest value. This implies that the normalized index takes on values between 0 and 1. The mean and standard deviation of this normalized index are 0.066 and 0.15, respectively.

5.1 OLS and fixed-effects regressions

Our baseline results are presented in Table 4 below. Column 1 contains the most basic regression, where we just regress the log of value-added on the log of total capital and the log of the total hours worked (our quantity measure of labor input). Note that the results are largely consistent with constant returns to scale in the production function. The coefficient of labor is around 0.6 and strongly significant. Furthermore, the size of the estimated coefficient of capital (0.441) is only marginally higher than the values found by, for example, Stiroh (2005).

In column 2, we split the capital variable into ICT capital and non-ICT capital. Again, the results are comparable to those found in Stiroh (2005). Both coefficients are significant, and the sum of the two coefficients is approximately equal to the coefficient of the aggregated capital variable in column 1. However, the coefficient of non-ICT capital is only around two times larger than the coefficient of ICT capital (0.15), although the average amount of non-ICT capital in production (and hence its revenue share) is more than four times the amount of ICT capital (cf. Table 3). This could, as in Stiroh (2005), indicate that ICT capital is associated with higher returns than non-ICT capital.

In columns 3 and 4, we add the robot-intensity index. The estimated coefficient of the robot-intensity index is significant at the 5% level when aggregate capital is used as in column 3. When non-ICT and ICT capital enter separately (column 4), it is seen that the significance level drops to 10%. However, this is also true for ICT capital, suggesting that industry × country cells with high ICT capital also have a high robot-intensity index and *vice versa*, that is, the fall in significance is due to a multicollinearity problem.

The results in columns 3 and 4 are consistent with the hypothesis that industrial robots have an additional effect on value-added compared to other types of non-ICT capital. The higher the concentration of robots in the non-ICT capital stock, the higher is productivity. Specifically, the point estimate of the robot-intensity index equals 0.44 in column 4. This value represents the marginal rate-of-return to *RI* and implies that an increase of one standard deviation (0.15) in the robot-intensity index is associated with 6.6% higher TFP. Alternatively, as the average industry has a value of 0.066 of the robot index, it implies that its productivity level is 2.90% (0.44 × 0.066) higher than it would be in the case without any robots.

Furthermore, adding the robot-intensity index to the regression raises the coefficient of the non-ICT capital variable and lowers the coefficient of the ICT capital variable in column 4, so that their ratio is now more in line with the ratio of non-ICT to ICT capital in production. In other words, when taking the amount of robots in non-ICT capital into account, the importance of ICT capital in production decreases. This is a potentially interesting finding, which might point to an omitted-variable bias in studies ignoring the robot intensity.

As discussed in Section 3, the OLS estimates in columns 1–4 are potentially biased and inconsistent. One potential cause of this is quality differences in the stock of industrial robots across industries and countries, which are not captured by our robot-intensity index, cf. our discussion in Section 1. Another potential cause of this is differences in productivity across industry-country cells that also affect the robot intensity, cf. our discussion in Section 3. This could happen if more productive industries (or less productive industries) chose to use more or less industrial robots.

Table 4. Productivity and automation, OLS and fixed effects estimations

	1	2	3	4	5	6	7	8
Estimation method	OLS	OLS	OLS	OLS	FE	FE	FE	FE
Persons engaged (L)	0.601***	0.582***	0.586***	0.577***	0.455***	0.454***	0.429***	0.427***
	(0.087)	(0.081)	(0.083)	(0.078)	(0.098)	(0.099)	(0.099)	(0.100)
Capital ($K + C$)	0.441***		0.465***		0.198		0.248*	
	(0.046)		(0.042)		(0.124)		(0.125)	
Robot intensity (RI)			0.475**	0.443*			0.604**	0.591**
			(0.218)	(0.234)			(0.231)	(0.238)
ICT capital (C)		0.149**		0.108*		0.046		0.049
		(0.071)		(0.063)		(0.077)		(0.076)
Non-ICT capital (K)		0.295***		0.354***		0.135		0.181
		(0.084)		(0.073)		(0.122)		(0.123)
R^2	0.984	0.985	0.985	0.986	0.341	0.338	0.362	0.359
Number of observations	356	356	356	356	356	356	356	356

Note: Data are for the period 2004–2007. The dependent variable in all columns is the log of valued added per worker. The robot-intensity index is normalized by the observation with the highest value, implying that it takes on values between 0 and 1, with a mean of 0.066 and a standard deviation of 0.15. See main text and Table 3 for a description of the remaining explanatory variables. The industry "Other manufacturing products" is excluded for Sweden because values for non-ICT capital are not available. 2007 values for Japan are missing and replaced by 2006 values, except in the case of industrial robots. Time dummies are included in all columns, and industry and country dummies are included in columns 1–4. Standard errors in brackets are clustered at the industry × country level and robust to heteroskedasticity and autocorrelation of unknown form. R^2 in columns 5–8 is the within R^2 value. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Source: EUKLEMS and International Federation of Robotics (2011).

Therefore, columns 5–8 present estimates similar to those in columns 1–4, but now adding fixed effects at the industry × country level, were implying that the coefficients are identified from changes over time within industry × country cells.[6] This significantly lowers the estimate of the coefficients of both ICT and non-ICT capital in columns 6 and 8, and the coefficients now become insignificant. It also reduces the coefficient of the overall capital variable in columns 5 and 7, although it stays significant at the 10% level in column 7. These findings may reflect multicollinearity between (changes in) the two types of capital. Moreover, physical capital enters positively and significantly when equation (7) is estimated without year dummies. This indicates that it is hard to distinguish between the effects of year dummies (a time trend) and the changes in physical capital in the short-time window used.

The point estimates of the robot-intensity index remain high and significant in columns 7 and 8. Furthermore, estimates are higher in magnitude than those of columns 3 and 4. However, the obtained estimates under OLS and fixed effects are not significantly different. This suggests that although a bias may be present in the OLS regressions, it is not to an extent that changes the qualitative conclusions.[7] Taken together, the results presented in Table 4 strongly supports the idea that a use of industrial robots adds to TFP through a more advantageous composition of non-ICT capital.

5.2 Robustness checks

An alternative way to handle the potential quality differences of industrial robots and to remove the effects of time-invariant productivity differences across industry-country cells is to estimate equation (7) in first differences. This also allows us to utilize that we have information about the shipment of industrial robots to an additional five countries. As these countries are low-intensive users of industrial robots (International Federation of Robotics, 2011), the depreciation of their current stocks of robots is likely to be limited. Therefore, we can use the shipments as proxies for the changes in their stocks of robots in first-difference estimation. This approximation would not work for more intensive robot-using countries, where the depreciation of the current stock would be relatively more important.

In column 2 of Table 5, we present the results of first-difference estimation where we use changes between 2004 and 2007 for all variables. Using 3-year differences instead of 1-year differences, reduces the importance of random measurement error and hence the risk of attenuation bias. On the other hand, endogeneity problems may become more severe by using 3-year differences, because the transformed error term includes more time periods (Draca *et al.*, 2009). In column 1 of Table 5, we have included the fixed-effects specification from column 8 of Table 4 for comparison purposes.

Compared to the fixed-effect specification, the robot-intensity coefficient increases slightly and remains strongly significant in the first-difference specification. Furthermore, the non-ICT capital coefficient increases and becomes significant at the 1% level, whereas the coefficient to ICT capital remains insignificant.

As discussed above, the robot-intensity index is not adjusted for quality changes in industrial robots over time. Using the quality index for industrial robots of Figure 4, we know that the average annual improvement in quality is 6.2% for the period 1990–2005 and that it is 2.3% for the last 5 years up to 2005. We can perform a back-of-the-envelope calculation to assess the impact on the estimation results for the first-difference estimation of not adjusting for quality improvements. If we assume that ρ_t, the *annual* quality change in robots, and $\Delta_1 R_t$, the *annual* net change in the number of robots, are constant over time, that is, $\rho_t = \rho$ and $\Delta_1 R_t = \Delta_1 R$, we can obtain a quality-adjusted measure of the three-year change in the number of robots, which is equal to $\Delta_3 R_t = 3\Delta_1 R * \left(\left((1+\rho) + (1+\rho)^2 + (1+\rho)^3\right)/3\right)$. This measure can then be used to recalculate the change in the

6 The applied 4-year period may be considered to be a relatively short period for using fixed effects and first differences. The main argument for using this period is to avoid estimates to be too affected by quality changes in industrial robots that we do not account for. The longer a time window we use, the more problematic is the quality issue. To investigate the robustness of the estimated results, we have estimated Table 4, columns 5–8 using the 6-year period using data for 2002–2007. The obtained point estimates for the fixed-effects regression are of similar size and significance as the results of Table 4. The results are available upon request.

7 As an alternative to the model in (7), where we use value added as the dependent variable, we can use a model with gross output on the left-hand side and then include intermediate inputs as an extra regressor. Using this approach and the fixed-effect specification, the coefficient of the robot-intensity index is still significant and positive, which brings additional support to the results in Table 4.

Table 5. Productivity and automation, alternative estimation methods

Estimation method	1 FE	2 FD	3 Median-FD	4 WLS-FE	5 WLS-FE
Persons engaged (L)	0.427***	0.824***	0.786***	0.404***	0.405***
	(0.100)	(0.190)	(0.178)	(0.097)	(0.098)
Robot intensity (RI)	0.591**	0.785***	0.627**	0.522**	0.524**
	(0.238)	(0.255)	(0.298)	(0.213)	(0.211)
ICT capital (*C*)	0.049	0.023	−0.013	0.065	0.062
	(0.076)	(0.053)	(0.049)	(0.078)	(0.078)
Non-ICT capital (*K*)	0.181	0.425***	0.381***	0.169	0.158
	(0.123)	(0.096)	(0.088)	(0.121)	(0.120)
R^2	0.359	0.392	0.207	0.355	0.349
Number of observations	356	139	139	356	356

Note: Data are for the period 2004–2007. The dependent variable in all columns is the log of valued added per worker. See main text and Table 3 for a description of the explanatory variables. The industry "Other manufacturing products" is excluded for Sweden because values for non-ICT capital are not available. 2007 values for Japan are missing and replaced by 2006 values, except in the case of industrial robots. Column 1 is identical to column 8 of Table 4. All variables in columns 2 and 3 are measured as the difference between 2004 and 2007, except in the case of Japan. Time, industry, and country dummies are included in columns 1, 4, and 5. The estimation method in column 3 is median regression, whereas the estimation method in columns 4 and 5 is WLS. In column 4, the log of the wage bill is used as weights, and in column 5, the log of total employment is used. Standard errors in brackets in columns 4 and 5 are clustered at the industry × country level; standard errors for all columns are robust to heteroskedasticity and autocorrelation of unknown form. ***, and ** indicate significance at the 1%, and 5% level, respectively.

Source: EUKLEMS and International Federation of Robotics (2011).

robot index: $RI_{t+3} - RI_t = R_{t+3}/K_{t+3} - R_t/K_t = (R_t + \Delta_3 R_t)/K_{t+3} - R_t/K_t$. Using this measure in the small sample of 89 country × industry observations for the first-difference estimation, the point estimate becomes $\delta = 0.565$ for $\rho = 0$, $\delta = 0.547$ for $\rho = 2.3\%$ and $\delta = 0.517$ if $\rho = 6.2\%$. The main insight of this back-of-the-envelope robustness analysis is thus that the obtained point estimate is relatively robust to small, but realistic, increases in the quality of industrial robots.[8]

In sum, we find that taking these changes into account in the first-difference estimation do not imply important changes in the point estimate for the robot-intensity index. This result provides further evidence for the result that quality changes do not contaminate the obtained qualitative results when examining a short-time period.

The results of the first-difference specification may be partly affected by the presence of outlier observations. To check for the importance of this, column 3 reports results when using a median-regression approach for the first-difference specification in column 2, as this approach is more robust towards the presence of extreme observations. The results are, however, very similar to those of column 2, which suggests that the observed relationship between productivity and the robot intensity is not driven by outlier observations.

So far, all observations have been given the same weight in the regressions. Thus, a small industry in a small country, such as *textiles, leather, and wearing apparel* in Denmark, carries as much importance for the estimated regression coefficients as a large industry in a large country, such as *motor vehicles and other transport equipment* in Germany. An alternative approach would be to estimate our model using WLS, where the weights are the labor input in the different industry-country cells. This approach is used in Table 5, columns 4 and 5. In column 4, we use the log of the wage bill as weights, whereas in column 5 we use the log of total employment. The latter approach is similar

8 If the depreciation of robots consists of low-quality vintages, we may not control in full for robot quality even though we use a short window of time. We, however, consider this effect to be negligible, which can be explained using the logic of the 3-year change in the robot stock; the measure that we use in the first-difference estimation. The 3-year change equals net-investments in robots during the 3 years. That is, net-investments equal gross-investments − depreciations of robot. IFR assumes that the average operating service life of an industrial robot is 12 years. This implies that we have to deduct gross-investments from 1993 to 1995 (depreciations) from gross-investments from 2005 to 2007 when calculating the 3-year change between 2004 and 2007. If quality improvements are important the old gross-investments should have lower weights to take quality improvements into account. However, investments in robots were at a low-level back in the early 1990s, and therefore, we believe that it is safe to disregard this aspect.

Table 6. Productivity, automation, and worker quality

Estimation method	1 FE	2 FD	3 Median-FD	4 WLS-FE	5 WLS-FE
Share of skilled workers (S)	0.517**	0.335	0.259	0.530*	0.521*
	(0.260)	(0.398)	(0.344)	(0.267)	(0.264)
Persons engaged (L)	0.448***	0.787***	0.743***	0.428***	0.427***
	(0.101)	(0.184)	(0.201)	(0.097)	(0.097)
Robot intensity (RI)	0.515**	0.765***	0.586*	0.445**	0.448**
	(0.231)	(0.260)	(0.332)	(0.200)	(0.200)
ICT capital (C)	−0.004	−0.002	−0.022	0.015	0.012
	(0.077)	(0.065)	(0.060)	(0.077)	(0.078)
Non-ICT capital (k)	0.194*	0.442***	0.391***	0.181	0.170
	(0.114)	(0.099)	(0.099)	(0.113)	(0.113)
R^2	0.386	0.397	0.214	0.383	0.377
Number of observations	356	139	139	356	356

Note: Data are for the period 2004–2007. The dependent variable in all columns is the log of valued added per worker. See main text and Table 3 for a description of the explanatory variables. The industry "Other manufacturing products" is excluded for Sweden because values for non-ICT capital are not available. 2007 values for Japan are missing and replaced by 2006 values, except in the case of industrial robots. The share of skilled workers is imputed for 2006 and 2007: first coefficient values are estimated by OLS using data from 1970 to 2004, and then, the values for 2006 and 2007 are predicted. All variables in columns 2 and 3 are measured as the difference between 2004 and 2007, except in the case of Japan. Time, industry, and country dummies are included in columns 1, 4, and 5. The estimation method in column 3 is median regression, whereas the estimation method in columns 4 and 5 is WLS. In column 4, the log of the wage bill is used as weights, and in column 5, the log of total employment is used. Standard errors in brackets in columns 1, 4, and 5 are clustered at the industry × country level; standard errors for all columns are robust to heteroskedasticity and autocorrelation of unknown form. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Source: EUKLEMS and International Federation of Robotics (2011).

to that used by Stiroh (2005). In both columns, we estimate the fixed-effect specification from column 1, and, overall, the results are very similar. This supports that the previous results were not driven by small industry-country cells. In particular, the coefficient of the robot-intensity index is strongly significant in both columns 4 and 5.

5.3 Human capital

In order to analyze to which extent changes in worker quality drives the results, we have also estimated the model including the share of skilled workers, cf. equation (7). This share increases from 75.8% in 2004 to 80.4% in 2007 on average in our data. The results of the estimation are shown in Table 6.

First, note that the share of skilled workers has a positive impact on productivity in all regressions. However, the significance level varies across the five specifications. Second, the robot-intensity index still has a robust and significant positive effect on productivity when the skilled share is included in the estimations. However, the coefficient of the robot-intensity index is somewhat smaller than in Table 5. It decreases by approximately 0.1 but is still in the range of 0.45–0.77. Specifically, the point estimate equals 0.52 in column 1. This magnitude implies that an increase of one standard deviation in the robot-intensity index is associated with 7.8% (0.52 × 0.15) higher productivity. This should be compared with 8.9% (0.59 × 0.15) that is the increase in productivity based on the point estimate of Table 4, column 8 when the skilled share is not included in the regression.

5.4 Instrumental-variable estimations

Although the results in Tables 4 and 5 point to a strong and positive correlation between our robot-intensity index and value-added when controlling for capital, labor input and time-invariant productivity differences across industries and countries, we cannot be sure that this reflects a causal effect of the industrial robots on productivity. There might still be a risk that unobserved shocks to productivity also affect input choices (including the use of robots). This could be the case if industries that are hit by positive shocks during the observed period invest more heavily in robots. In that case, the coefficient of the robot-intensity variable will be upward biased.

To deal with this, we can use an instrumental-variable specification. A common approach in the literature is to estimate the model in levels and then use the lagged first differences of the explanatory variables as instruments (Stiroh,

Table 7. Productivity and automation, instrumental variables, and system-GMM estimations

Estimation method	1 OLS	2 FE	3 IV-level	4 IV-FD	5 SYS-GMM1	6 SYS-GMM2
Persons engaged (L)	0.577***	0.427***	0.577***	0.196*	0.469***	0.422**
	(0.078)	(0.100)	(0.075)	(0.109)	(0.084)	(0.182)
Robot intensity (RI)	0.443*	0.591**	0.489***	0.768**	0.619***	0.688***
	(0.234)	(0.238)	(0.171)	(0.191)	(0.163)	(0.214)
Non-ICT capital (C)	0.354***	0.181	0.361***	0.248**	0.396***	0.360**
	(0.073)	(0.123)	(0.070)	(0.110)	(0.071)	(0.155)
ICT capital (K)	0.108*	0.049	0.103*	0.125**	0.111**	0.210*
	(0.063)	(0.076)	(0.061)	(0.052)	(0.050)	(0.122)
R^2	0.986	0.359	0.985	0.198		
N	356	356	356	356	356	356
Number of instruments	0	0	2	1	3	9
R^2 for excluded IV for						
Robot intensity (RI)			0.42	0.13		
Under identification						
Statistic			7.358	4.561		
P-value			0.025	0.033		
Weak identification						
Statistic			32.984	4.571		
RI endogenous						
Statistic			4.818	3.675		
P-value			0.010	0.058		
Hansen test						
Statistic			1.540		13.44	38.42
P-value			0.215		0.020	0.276
Ar2						
Statistic	4.86		4.81	0.85	0.86	0.84
P-value	0.00		0.00	0.39	0.39	0.40

Note: See Table 4. In columns 3 and 4, two-stage least square estimation are used. In columns 5 and 6, GMM estimation are used. Instruments used are the following: In column 3 (IV-level): (RI(t) − RI(t−3)) and (RI(t−1) − RI(t−4)). Test for redundancy of the extra instrument shows that the variable adds information. In column 4 (IV-FD): RI(t−1) − RI(t−4). In column 5 (SYS-GMM1): as in IV-level and IV-FD. In column 6 (SYS-GMM2): as in SYS-GMM1 for RI for labor, and the two capital variables $x(t-1) - x(t-2)$ and $x(t-2) - x(t-3)$ is used for the level equation and $x(t-2)$ and $x(t-3)$ for the difference equations, where x refers to the specific explanatory variable. The test results are shown for the following test: LM test for *underidentification* (H0: RI is not identified by the exclude IV). F test for *weak identification* (H0: small correlation between RI and the excluded IV). F test for *RI endogenous* (H0: coefficient on RI is equal to zero). *Hansen test* for validity of instruments (H0: instruments are valid). Test for serial correlation in the differenced residuals, AR(2) test for AR(1) in levels. Stat refers to the test statistic and P to the probability. We have also used other test, worth mentioning is Difference-in-Hansen, which have been used to understand which models was the best to use. For details on the test see Baum *et al.* (2007) and Roodman (2007a,b). ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Source: EUKLEMS and International Federation of Robotics (2011).

2005). The idea behind these instruments is that previous changes in industrial robots can explain the current level in these variables, but are (hopefully) uncorrelated with current shocks to productivity. This, of course, presupposes that shocks are not too long-lived, which might be a dubious assumption. More precisely, validity of the instruments requires that the lagged change in industrial robots is uncorrelated with the error term in (7). This assumption will be tested below.

In columns 1 and 2 of Table 7, we first show the key results from Table 4. In column 3, a model in levels is estimated assuming that the labor and capital variables are strictly exogenous. Assuming that the robot-intensity index is predetermined, we use 3-year difference as instrument and for efficiency, the first lag is also added. Similar results are obtained if we assume that robot-intensity is endogenous. The results are similar to those in column 1. Examining post-estimation test, the partial R^2 for the excluded instruments is high, 0.42, the null hypothesis of weak identification is rejected, and the Hansen's test shows that the instruments are valid. Hence, all common tests are satisfied. However, testing for autocorrelation in the errors shows that the productivity shocks are serially correlated which might lead to coefficients being biased or falsely significant at worst. This is most likely due to not removing the effects of time-invariant productivity differences across industry-country cells.

This leads us to use a model in differences, column 4, still instrumenting the robot-intensity index. All the covariates have positive significant coefficients, but they are somewhat lower (except for ICT capital and robot intensity) than in columns 1 and 3. This is due to all the series being very persistent.

A better alternative is, therefore, to combine the two IV equations into a system often labeled "system GMM".[9] Results for the "system GMM" is shown in column 5. To avoid the problems of instrument proliferation (the main concern of "system GMM"), only the instruments used in the two earlier columns (IV-level and IV-FD) are used. The coefficients of all the variables are significantly positive and between those of the IV-level and IV-FD, leaning toward the IV-level, except for the coefficients of the robot-intensity index that are in the middle. Several tests including the Hansen test, however, indicate problems with the specification of the model. The difference-in-Hansen test (not shown) indicates that the problem is the assumption of only the robot-intensity index not being strictly exogenous.

In column 6, we, therefore, relax the strictly exogenous assumption for labor input and the capital variables. All coefficients are significantly positive and relatively close to the coefficients in the other columns.[10] In the notes to the table, we have specified the applied instruments for each variable. To limit problems of instrument proliferation, we have limited the number of lags and have collapsed some of the instrument sets (Roodman, 2007a).

In sum, independent of the specific instrumental-variable approach used, we find that the IV point estimates are of similar magnitude as the OLS and FE estimates, that the IV-point estimates are significantly different from zero, and that the instrumental variables are not weak. We, therefore, conclude that there is relatively strong support for a causal relationship between higher concentrations of robots in the non-ICT capital stock and higher productivity.

6. Other aspects of industrial robots

The previous section revealed a relatively robust relationship between the use of industrial robots and productivity. This indicates that robots might help foster productivity growth in the manufacturing sector of developed countries. This gives rise to two associated questions. The first is whether the reallocation of manufacturing activities from developed countries to developing countries also leads to investments in industrial robots in the former countries. The second is whether productivity growth based on increased automation will also bring additional jobs and/or higher wages to developed countries, or whether this development will be at the expense of additional jobs and/or wage growth. In this section, we provide some first answers to these questions.

6.1 Import competition and investments in robots

An important consequence of the relocation of manufacturing activity to the developing world is illustrated in Bloom *et al.* (2016) who present descriptive statistics for the share of all imports in the Europe and the United States from low-wage countries. Here, it is shown that the share of imports that originates from the developing world was less than 5% in 1990 surging to more than 15% in 2007. In this development, China has played a crucial role. Moreover, it is found that firms that are exposed to competition from Chinese imports innovate more than firms that are not exposed or exposed to a lower degree.

Similarly, we might expect firms in the developed world that are exposed to higher pressure from international competition from developing countries to invest more heavily in industrial robots. If this is the case, we would expect to observe the largest increases in the robot-intensity index in industries and countries where imports from low-wage countries have increased the most.

In Table 8, we, therefore, test whether import competition from low-wage countries has a positive and significant effect on the robot-intensity index using the same estimation techniques as in Tables 5 and 6. That is, we regress the robot-intensity index on the capital and labor variables as well as a variable measuring the import competition from

9 The "system" GMM estimator is designed for a short panel with many ID, independent variables that are not strictly exogenous, fixed effects and heteroscedasticity, and auto-correlated errors.

10 If assuming that RI is endogenous the instrument for the difference equations are somewhat weak; however, if assuming that RI is predetermined the partial R-squared in a regression of difference in RI on the instruments are significantly improved. The Systen GMM regressions results for the two cases are almost exactly the same, and the test has similar outcomes.

Table 8. Robot intensity and import competition from China

Estimation method	1 FE	2 FD	3 Median-FD	4 WLS-FE	5 WLS-FE
Import competition from China (imp^{CHN})	0.020***	0.019***	0.005***	0.020**	0.021**
	(0.007)	(0.006)	(0.002)	(0.008)	(0.008)
Persons engaged (L)	−0.046	0.087	0.045**	−0.052	−0.053
	(0.044)	(0.066)	(0.018)	(0.044)	(0.045)
ICT capital (C)	−0.004	0.011	0.008	−0.005	−0.005
	(0.016)	(0.014)	(0.005)	(0.016)	(0.017)
Non-ICT capital (K)	−0.081	−0.032	−0.019**	−0.081	−0.082
	(0.053)	(0.032)	(0.008)	(0.053)	(0.056)
R^2	0.115	0.105	0.064	0.110	0.111
Number of observations	356	129	129	356	356

Note: Data are for the period 2004–2007. The dependent variable in all columns is the robot-intensity index. Import competition from China is measured as log or Δlog of Chinese imports to total imports. This variable is lagged two periods. See main text and Table 3 for a description of the other explanatory variables. The industry "Other manufacturing products" is excluded for Sweden because values for non-ICT capital are not available. 2007 values for Japan are missing and replaced by 2006 values, except in the case of industrial robots. All variables in columns 2 and 3 are measured as the difference between 2004 and 2007. Time, industry, and country dummies are included in columns 1, 4, and 5. The estimation method in column 3 is median regression, whereas the estimation method in columns 4 and 5 is WLS. In column 4, the log of the wage bill is used as weights, and in column 5, the log of total employment is used. Standard errors in brackets in columns 1, 4, and 5 are clustered at the industry × country level; standard errors for all columns are robust to heteroskedasticity and autocorrelation of unknown form. ***, and ** indicate significance at the 1%, and 5% level, respectively.

Source: EUKLEMS, International Federation of Robotics (2011), and WIOD.

China. The latter variable is constructed as the log of the proportion of total imports in industry i and country j that originates from China.

Table 8 confirms that industries that have been exposed to a large increase in Chinese import competition have increased the robot intensity by more than industries with more modest increases in import competition. The finding is relatively robust across the different estimation methods in Table 8. Only for the median regression in first differences (column 3) do we find a lower (but still significant) point estimate.[11]

To get a sense of the economic significance of these estimates, one should bear in mind that the average increase in Chinese import competition is around 0.47 resulting in an increase of 1% point (0.02×0.47) in the robot-intensity index for the average industry between 2004 and 2007, which should be compared with an average initial robot intensity of 6.68% in 2004. Moreover, for the 75th (90th) percentile, we find an increase of 0.98 (1.29) leading to an increase of 2% (2.6) points in the robot-intensity index.[12]

These results thus support the hypothesis that industries in developed countries increase their robot intensity in response to increasing Chinese import competition and that Chinese import competition may have played an important role in increasing the robot intensity in the period considered. Combined with the results established in Section 5, this suggests that industries that have been exposed to competition from low-wage countries have improved their productivity by investing in industrial robots.[13]

11 Our estimation uses a lag of 2 years for Chinese import competition. This implies that we study the impact on the robot intensity between 2004 and 2007 from changes in Chinese import competition during the period 2002–2005.

12 Another potential driver for investments in industrial robots is changing relative costs of robots. If automation costs fall and the robot capability rises, then firms should substitute industrial robots for labor in production. However, working more technical machines, whilst it may reduce labor headcount, also requires higher quality labor input. Changes in relative wages may be another important driver for an increasing use of robots, such that a large increase in the relative wage for unskilled workers may increase the use of robots. We have also included log wages of unskilled workers, medium-skilled workers, and high-skilled workers. There is some empirical support for higher use of automation in industries that experience high increases in unskilled wages.

13 We do not apply the measure of Chinese import competition as an instrument for the robot intensity because we cannot convincingly rule out effects running through omitted variables, that is, the exclusion restriction is not fulfilled in this case. Bloom et al. (2016) find that firms exposed to large increases in Chinese import competition also have larger

Table 9. Automation, wages, and total employment

Dependent variables	1 Log (average wage)	2	3 Wage share	4	5 Log (total employment)[1]	6
Estimation method	**FE**	**FD**	**FE**	**FD**	**FE**	**FD**
Persons engaged (L)	0.282***	0.648***	−0.083	−0.055		
	(0.080)	(0.175)	(0.087)	(0.089)		
ICT capital (C)	−0.032	0.064*	−0.055	0.025	−0.001	−0.011
	(0.048)	(0.036)	(0.047)	(0.028)	(0.013)	(0.034)
Non-ICT capital (K)	0.292***	0.490***	0.091	0.047	0.074***	0.147***
	(0.083)	(0.084)	(0.063)	(0.048)	(0.024)	(0.042)
Robot intensity (RI)	0.363*	0.726***	−0.160	−0.059	0.088	0.198
	(0.190)	(0.263)	(0.129)	(0.140)	(0.080)	(0.158)
R^2	0.393	0.573	0.087	0.032	0.445	0.114
Number of observations	356	139	356	139	356	139

Note: Data are for the period 2004–2007. The dependent variable in columns 1 and 2 is the log of the average wage rate; in columns 3 and 4, it is the wage share defined as the total wage sum relative to value-added; and in columns 5 and 6, log of total employment is used. Explanatory variables are the log of total ICT and non-ICT capital (not per worker) and the robot-intensity index. The industry "Other manufacturing products" is excluded for Sweden because values for non-ICT capital are not available. 2007 values for Japan are missing and replaced by 2006 values, except in the case of industrial robots. Time dummies are included in all columns. Standard errors in all columns are clustered by industry and country. [1]Explanatory variables are the log of total ICT and non-ICT capital (not per person) and the robot-intensity index. ***, and * indicate significance at the 1%, and 10% level, respectively.

Source: EUKLEMS and International Federation of Robotics (2011).

6.2 Robots, wages, and employment

This section looks briefly at the relationship between the use of robots, on the one hand, and wages and employment on the other hand. The results are presented in Table 9. All regressions are carried out using fixed effects and first differences.

In columns 1 and 2, we regress the log of the average wage in an industry-country cell on the log of ICT and non-ICT capital per worker, the log of total employment and the robot-intensity index. In both regressions, we find a positive and significant effect of the robot-intensity index, and the size of the estimated coefficient is remarkably robust across the two regressions. Thus, industry-country cells that have (or get) a higher intensity of robots also have (or get) higher average wages. This could reflect both an individual effect (individuals with a given skill level are paid more in these industries) or a composition effect (these industries hire more skilled persons). Without individual-level data, we are not able to determine which explanation is the most important.

Columns 3 and 4 are similar to columns 1 and 2, except that we now use the wage share as the dependent variable. In this case, we find no effect of the robot intensity. Coefficient estimates are all highly insignificant. Thus, there seems to be no connection between the use of robots and the share of value-added going to workers. In other words, robots are not diminishing the labor share of value-added.

Finally, columns 5 and 6 use the log of total employment in an industry-country cell as the dependent variable. In this case, we use the log of total ICT and non-ICT capital (not per worker) on the right-hand side together with the robot-intensity index. We do not find any significant relationship in this case. If we instead use the log of the number of robots rather than the robot-intensity index, the estimated coefficient becomes significant in both regressions (results not reported). Although, we are careful not to give this a causal interpretation, it is at least an indication that robots do not crowd out labor at the industry level—and may even seem to affect employment positively.

In sum, we find that a higher robot-intensity in non-ICT capital is associated with higher average wages and perhaps also higher employment—and it does not seem to diminish labor's share in value-added. This is good news for those who fear that robots will crowd out jobs and put a downward pressure on wages. The results are also consistent with results found in, for example, Autor *et al.* (1998) and Krusell *et al.* (2000).

increases in their innovation activities as measured by counts of patents and number of computers per worker. In our regressions, we include measures of IT, but we do not include patents.

7. Conclusion

Policy makers and industry confederations in the developed world have for years been interested in finding methods to stop the offshoring of manufacturing jobs, and they have even attempted to re-shore manufacturing activities and jobs lost to the developing world. The main reason is that the manufacturing sector is believed to be essential to ensure continued welfare improvements. In particular, this sector is responsible for a large fraction of the economic activity, contributes significantly to all innovations, and leads the way on trade.

In this article, we have analyzed three important and related questions: (i) Can industrial robots help raise the productivity in the manufacturing sector? (ii) Does the level of competition from the developing world explain the increased use of industrial robots in developed countries?, and (iii) Will the increased use of robots crowd out workers and put pressure on average wages as feared by many? The answers we provide to these questions show that industrial robots may, in fact, help revive the manufacturing sector in the developed part of the world.

Our empirical study is carried out using a panel dataset covering 10 manufacturing industries in nine industrialized countries. We illustrate that labor productivity has increased by more than 35% over the period from 1997 to 2007 in the manufacturing sector in the developed world, whereas employment has decreased. By using a Cobb–Douglass production function, we show that the improvement in productivity is related to investments in industrial robots. Moreover, our results indicate that industrial robots have an additional effect on productivity compared to other types of non-ICT capital. This strongly supports the idea that industrial robots add to TFP through a more advantageous composition of non-ICT capital.

On a more technical note, we report two importing findings. First, as quality-adjusted measures of industrial robots do not exist, that is, an old robot and a new robot are considered equally productive when constructing stocks of industrial robots, quality differences and changes may contaminate empirical results. To control for this, we perform fixed-effects and first-difference estimations within a short-time window. Second, we perform instrumental-variable regressions to investigate whether the estimated relationship between industrial robots and productivity is causal.

Next, our data confirm that industries with higher international competition pressure from developing countries invest more heavily in industrial robots. Combining this with our first finding, this suggests that developed countries have reacted to increasing competition by adopting industrial robots and thereby improving their TFP.

Finally, there is no support in the data for decreasing wages or falling employment as a consequence of increased automation. In contrast, we actually find that an increase in industrial robots is associated with higher average wages and unchanged or even higher employment. The potential policy implications of our findings are significant: Initiatives that may induce further automation to have the potential to both raise productivity and create more (and better-paying) jobs. As the use of robots varies significantly across both the industrialized countries and the manufacturing industries, our findings strongly suggest that there is plenty of room for further automation in the battle for jobs and market shares in the manufacturing sector of the developed world.

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