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Robotization, employment and industrial growth
Intertwined across global value chains

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Abstract

The global economy is currently experiencing a new wave of technological change involving new technologies, especially in the realm of artificial intelligence and robotics, but not limited to it. One key concern in this context is the consequences of these new technologies on the labour market. This paper provides a comprehensive analysis of the direct and indirect effects of the rise of industrial robots and productivity via international value chains on various industrial indicators, including employment and real value added. The paper thereby adds to the existing empirical work on the relationship between technological change, employment and industrial growth by adding data on industrial robots while controlling for other technological advancements measured by total factor productivity (TFP). The results indicate that the overall impact of the installation of new robots did not statistically affect the growth of industrial employment during the period 2000–2014 significantly, while the overall impact on the real value added growth of industries in the world was positive and significant. The methodology also allows for a differentiation between the impact of robots across various industries and countries based on two different perspectives of source and destination industries across global value chains.

Keywords: robotization; digitalization; global value chains; total factor productivity; industrial growth; employment; value added

JEL-classification: D57, J21, L16, O14

1. Introduction

It is generally believed that the global economy is currently experiencing a new wave of technological change based on new disruptive technologies, especially in the realm of artificial intelligence (AI), machine learning and robotics, as well as others. Grouped together under headings such as Industry 4.0[1], one general interpretation is that an entire range of new technologies will make up the industrial revolution by fusing the physical, digital and biological worlds, impacting all disciplines, economies and industries (Schwab, 2017). This process is expected to revolutionize products and manufacturing processes by strongly impacting on factors of production and the generation and distribution of value added across sectors. Recent successes in the field of artificial intelligence (AI), such as DeepMind's AlphaZero defeating the world's leading chess-playing computer programme after having taught itself how to play in less than four hours, has intensified the debate about the challenges and opportunities of the 'Robot Age'[2] and whether mankind can win the race against the machine (Brynjolfsson and McAfee, 2011).

One key concern in this context are the consequences of such new technologies for the labour market. Estimates of the expected job losses due to new machines based on the high share of potentially automatable jobs which ranges from 47 per cent according to Frey and Osborne (2017) to less than 10 per cent according to the OECD (Arntz et al., 2016) with unspecified time spans over which this might occur.[3] [4] [5] It can be argued that technological change has historically created more jobs than it has destroyed over the longer term (on account of the process of creative destruction à la Schumpeter)[6].

[1] Industry 4.0 represented a so-called *Project for the Future* of the German Government, initiated in 2011 and developed into a platform in 2013. See: https://www.bmbf.de/de/zukunftsprojekt-industrie-4-0-848.html

[2] "AlphaZero AI beats champion chess program after teaching itself in four hours", *The Guardian*, 7 December 2017. https://www.theguardian.com/technology/2017/dec/07/alphazero-google-deepmind-ai-beats-champion-program-teaching-itself-to-play-four-hours.

[3] "According to our estimate, 47% of total US employment is in the high risk category, meaning that associated occupations are potentially automatable **over some unspecified number of years**, perhaps a decade or two." (Frey and Osborne, 2017, p. 265; emphasis added).

[4] The former result is based on a sample of 32 OECD countries, whereas the latter is based on the U.S. economy.

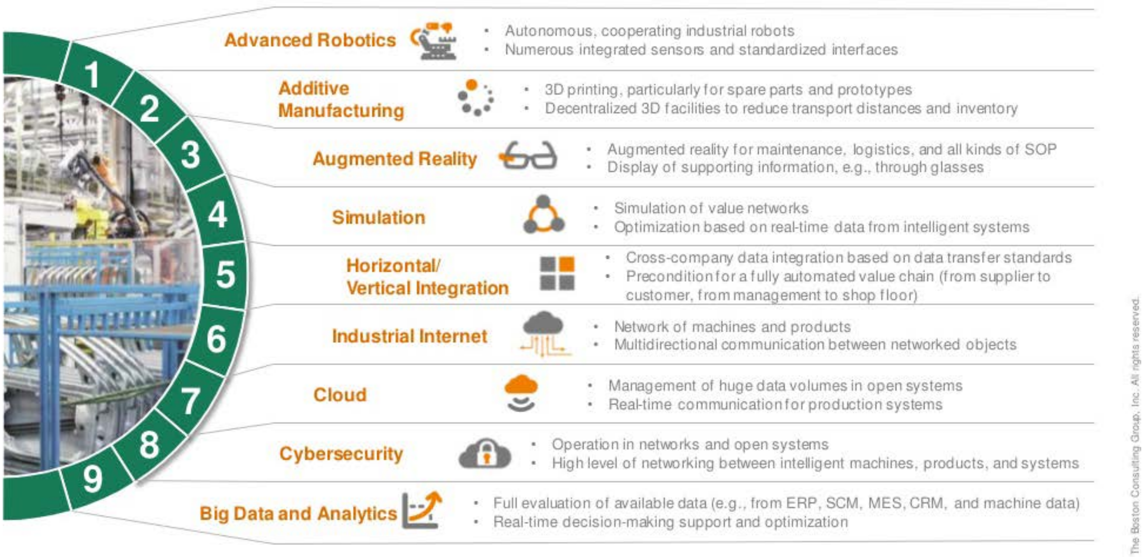
[5] The WTO (2018) argues that these new technologies could further reduce trade costs and could therefore contribute to trade and growth in the upcoming years. In general, however, the impact of different technologies on trade is ambiguous, as new production methods could also give rise to more localized production and/or a lesser scope for economies of scale.

[6] Concern about new technologies replacing jobs is actually an old one and can be traced back to the luddites in England of the early 19th century and in the economic literature to Keynes' essay on the *Economic Possibilities for our Grandchildren* (Keynes, 1930).

However, given the potentially disruptive nature of the anticipated new technological paradigm and the 'Fourth Industrial Revolution'[7] associated with it, extrapolating future developments from past experiences is difficult. The considerable uncertainty about the future technological trajectory and its economic consequences in periods of rupture poses a serious problem for researchers and policymakers. If, as is commonly assumed, the Fourth Industrial Revolution characterized by digitalization has arrived, the economic implications of the many new technologies (see e.g. Figure 1) need not necessarily be the same as those of the third technological wave, which was based on automation.

The limited information value of past linkages obviously poses a challenge for empirical analysis. This paper uses an indicator that can be interpreted as a link between the two industrial revolutions and is one possibility to deal with this challenge and the uncertainties involved. More precisely, data on the use of industrial multipurpose robots are used in this paper[8]. Such robots have played a major role in the automation era and will continue to be an important factor in the cyber-physical systems of the imminent Fourth Industrial Revolution. They are often subsumed under the key technologies of Industry 4.0 as illustrated in Figure 1.

Figure 1: Key technologies related to Industry 4.0



[7] The previous industrial revolutions were the steam-based industrial revolution in the early 19th century, the electricity-based second industrial revolution at the end of the 19th and early 20th centuries and the third industrial revolution dated to the 1970s, which brought about automation and digitalization (PwC, 2016).

[8] The disadvantage of limiting the analysis of employment effects to industrial robots as one specific technology is that only a partial, probably biased, picture will emerge. It could be biased because other technologies might impact entirely different industries in various directions and via different channels.

Note: SOP = Standard Operating Procedure; ERP= Enterprise Resource Planning; SCM=Supply Chain Management; MES=Manufacturing Execution System; CRM=Customer Relationship Management.
Source: Boston Consulting Group (2016).

There is obviously a broad range of other technologies that will shape the digital era, including additive manufacturing or big data analytics. All of these could affect labour markets and productivity by opening up new business opportunities and replacing labour. As the impact of these technologies will mainly be felt in the future (or have just begun to show some effects), they are difficult to gauge in an analytical study such as this one. Therefore, the focus here is on industrial robots which have been operational for several years.

The expansion of value added of a given industry may indirectly influence the employment figures in another sector through backward or forward linkages. For instance, a service activity might never actually use any industrial robots and hence, there will not be any direct effect on that activity from industrial multipurpose robots. Using industrial robots in the manufacturing of computers, electronics and optics, however, could result in productivity gains in that manufacturing industry, which translate into higher quality and less expensive products. Better products from this manufacturing industry will then be used in many other industries, for example, in the construction services industry, or in any other services activities not using robots. These more efficient intermediate inputs of production might lead to higher productivity gains in the services industries using them and might eventually lead them to create higher employment.

This paper provides a comprehensive analysis of the direct and indirect effects of industrial robots on various macro-economic indicators, including employment and real value added. The indirect effects capture both domestic and international linkages which were obtained from inter-country input-output tables. The paper thereby adds to the existing empirical work on the relationship between technological change, employment and industrial growth by using industrial robots, which was pioneered by Graetz and Michaels (2018), Abeliansky and Prettner (2017), and later, Acemoglu and Restrepo (2018).

The analysis of the implications of robots for labour markets is integrated into the long-run distributed lag framework developed by Autor and Salomons (2018) (henceforth AS). Most importantly, and in contrast to most of the literature, this paper focusses on emerging and transition economies. In addition, it extends the AS framework by including the effects of international input-output linkages in the analysis, which are limited to the domestic economy linkages in AS.

The remainder of this paper is structured as follows. Section 2 provides a brief overview of the related literature. Section 3 describes the data used and provides some descriptive evidence on the use of industrial robots. Section 4 explains the econometric model applied to the estimation results which are summarized in Section 5. Section 6 concludes.

2. Literature review

The analysis of technological progress and its effect on labour market outcomes such as employment (hours), wages and wage inequality has recently attracted increasing attention. Whereas the already cited seminal study by Frey and Osborne (2017) found that almost half of current U.S. jobs are at risk of being 'computerized', the estimates provided by Arntz et al. (2016) are far more conservative: rather than looking at occupations per se, they evaluated the potential 'automatability' of tasks within an occupation. In contrast to the findings of Frey and Osborne (2017), Arntz et al. conclude that only about 9 per cent of jobs are currently automatable. In addition, they emphasize that jobs of low-skilled workers are more susceptible to automation than high-skilled workers. Building on this finding, Nedelkoska and Quintini (2018) expanded the coverage of countries and occupational titles and calculated that around 14 per cent of jobs in OECD countries faced the risk of being 'highly automatable', defined as the risk of automation being above 70 per cent.

Graetz and Michaels (2018) used available data on robot use to estimate the effects on labour productivity growth, total factor productivity growth, output prices and employment. Their findings show that robots increase both labour productivity growth and total factor productivity (TFP) growth but tend to decrease output prices. While there seemed to be no effect of robot use on total employment, they find a negative impact of robots on the employment share of low-skilled workers. A recent report by the European Bank for Reconstruction and Development (EBRD, 2018) arrives at similar results for emerging economies: 'robotization' only has a small negative effect on employment for the entire economy. Workers with low levels of education are, however, disproportionately more affected by the adoption of robots. In another study, Acemoglu and Restrepo (2017) focus on U.S. local labour markets. They combine data from EU KLEMS and robot use to track the effects of increased exposure to robots on local labour markets from 1970 to 2007. Like Graetz and Michaels (2018), they find that the adoption of robots leads to large and robust declines in employment and wages.

Several studies address these issues from various theoretical perspectives. The most recent and one of the most comprehensive ones is the framework developed by Acemoglu and Restrepo

(2018). They develop a theoretical framework within which robots can substitute job-related tasks. Workers could, however, perform new tasks has and thus develop a comparative advantage over robots. In a model in which technological progress has replaced labour input but has resulted in increased capital requirements, Zeira (1998) demonstrates that only already highly productive countries use labour-saving innovations, which, in turn, reinforces the existing income differences between countries. Technological change may therefore explain why income differences exist between countries. Sachs and Kotlikoff (2012), Benzell et al. (2015) and Sachs, Benzell and LaGarda (2015) assume in their models that robots do not assist humans in the performance of their work, but rather fully replace them. They arrive to the conclusion that the introduction of robots would boost productivity in the short term but decrease wages and consumption in the long term. Sachs and Kotlikoff (2012), who presumed that "smart machines" will replace young and unskilled workers and favour old and skilled labour, find that only a generational (redistribution) policy could make the introduction of robots a profitable scenario for both generations. Similarly, Sachs, Benzell and LaGarda (2015) argue in favour of government redistribution in this scenario to counter the "immiserization" of future generations. Autor (2015) addresses these warnings by stating that in these models, "the fundamental threat is not technology per se but misgovernance"[9]. The problem is not the scarcity of jobs; rather, it is a distributional problem (should robots indeed make human labour unnecessary). He argues that an appropriate capital tax could help make technological progress a welfare-improving process for all groups of workers.

A related aspect is change in the wage structure of workers. The skill premia (the relative wage of high-skilled workers to low-skilled workers) rose over most of the second half of the last century, *despite* large increases in the supply of high-skilled workers. It seems that a 'skill-biased technological change' occurred, increasing the demand for high-skilled workers even more. Berman et al. (1998) were among the first to study the sources of the steadily increasing skill premia. In a similar vein, Krusell et al. (2000) modelled an economy based on a complementarity between a type of capital and high-skilled workers. The type of capital they used was information and communication technology (ICT) capital. Krusell et al. (2000) document a falling price of ICT capital. Thus, given such a capital-skill complementarity, a drop in the price of ICT capital would lead to an increased adoption of high tech by firms and subsequently to an increased demand for high-skilled workers to operate such machines. Michaels, Natraj and Van Reenen (2014) confirm these findings with newer data: industries with higher growth in ICT also show higher increases in demand for high-skilled workers and decreases in the demand for medium-skilled workers. Spitz-Oener (2006) finds that job requirements increased at the same time, i.e.

[9] See Autor (2015), p. 8.

the proportion of complex tasks increased. These changes in task structure have further raised the demand for skills in the labour market. Dao et al. (2017) conclude that industrial sectors specialized in routine activities tend to experience higher decreases in the labour share.

Koch et al. (2019) study the role of robots in Spanish firms during the period 1990–2016. Applying a difference-in-difference approach combined with a propensity score reweighting estimators, they find that larger firms in Spain, which have higher labour productivity and are less skill-intensive, adopted more robots than other firms. Moreover, the adoption of robots in Spanish firms led to larger output gains and lower labour costs. This resulted in higher job creation in firms that adopted robots.

The main reference point for this study is Autor and Salomons (2018). They estimate the effect of technological progress (preferring the term 'automation') on employment. Their work includes a systematic treatment of four different ways technological progress can affect the labour market: own-industry effects, upstream-industry effects, downstream-industry effects and final demand effects. In their framework, they quantify all these channels and conclude that total factor productivity (their proxy for technological progress) has negative direct effects on employment but positive indirect effects. In summary, the positive effects dominate, i.e. the overall effect of technological progress on employment is positive. In our study, we aim to combine the estimation framework of Autor and Salomons (2018) with the ideas of Graetz and Michaels (2018), Acemoglu and Restrepo (2017) and Koch et al. (2019). This allows us to shed light on the overall (direct and indirect) effects of robot use in industries on employment and wages in the economy.

3. Data and selected descriptive evidence

In this section, we briefly describe the data sources for this exercise and provide some descriptive evidence with respect to the use of robots by country groups and industries as well as sectoral developments.

3.1. Data

The econometric model draws on two major data sources. The first one is the 2016 version of the World Input-Output Database (WIOD) (Timmer et al., 2015) including data from accompanying

Socio-Economic Accounts (SEA)[10]. The second is the stock of industrial multipurpose robots database collected from the International Federation of Robotics (IFR, 2018)[11].

The data from the World Input-Output Database (WIOD) covers 43 countries and Rest of the World with a detailed industry structure comprising 56 industries[12] over the period 2000-2014. These are used to calculate the growth rates of value added and employment by industry and country as well as domestic and international forward and backward linkages used in the econometric exercise. Further, investment data are used to calculate capital stock at the country-industry level using the PIM method. This then allows the use of employment (*EMP*), nominal labour income (*W*), real capital stock (*K*) and (real as well as nominal) value added (*VA*) to calculate total factor productivity as given by

$$\begin{aligned}\Delta lnTFP_{cit} = \Delta\, ln\, VA_{cit}^{real} - \left(\frac{W_{cit}}{VA_{cit}^{nominal}} * \Delta lnEMP_{cit}\right) \\ - \left(\left(1 - \frac{W_{cit}}{VA_{cit}^{nominal}}\right) * \Delta lnK_{cit}^{real}\right)\end{aligned} \tag{1}$$

The IFR database provides data on industrial robots by industry for all major countries in the world. The term 'industrial robot' follows the definition of the International Organization for Standardization, namely an *"automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes"* (IFR, p. 29). The two key variables reported in the database are the number of robots newly installed in a year and the operational stock of robots which measures the number of robots currently deployed (IFR, 2018, p. 28).[13]

As the IFR data provides data for more aggregated industries compared to the WIOD, the latter are adjusted to match the industry structure of the IFR database. For this, the WIOD-SEA data are converted into US dollars using the yearly-averaged USD in local currencies obtained from the World Development Indicator (WDI) of the World Bank, augmented by the Penn World Table (Feenstra et al., 2015).

In the analysis, the countries covered in the WIOD are classified into four categories (as listed in Appendix Table A.1): advanced economies (corresponding to the sample used in Autor and Salomons, 2018), emerging economies, transition economies (comprising in our case only

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[10] Data available at: http://www.wiod.org/database/wiots16

[11] See: https://ifr.org/worldrobotics

[12] The industry structure is based on the NACE Rev. 2 industry classification and the SNA2008/ESA2010 methodology.

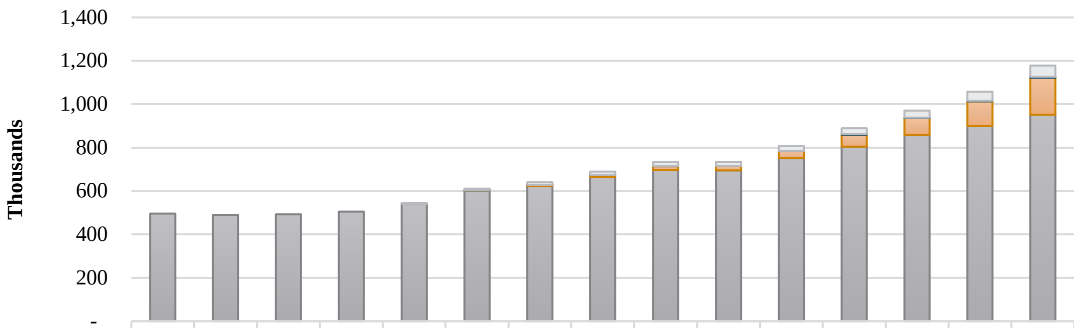
[13] In this report, the term 'stock' is used to indicate the number of industrial robots.

Bulgaria, Romania and Russia) and the remaining countries (including the Central and Eastern European economies).

3.2. Use of robots

The use and impact of such new technologies (proxied by the number of robots in this report) differ across countries and industries, with the advanced economies being forerunners in using industrial robots. As depicted in Figure 2, according to the data, around half a million industrial robots were installed and used in manufacturing, agriculture, mining and some services activities in advanced economies in 2000, while information on the stock of robots in other parts of the world was not recorded until 2004. From 2000 to 2014, investment in the stock of robots more than doubled, with over 950,000 robots being installed in advanced economies in 2014, 170,000 in emerging economies, under 4,000 in transition economies and only about 52,000 in the remaining countries.

Figure 2: Stock of industrial robots by country group in thousands – 2000-2014



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Rest	-	-	-	-	5	8	12	15	18	20	23	28	32	42	52
Transition	-	-	-	-	0	0	0	0	1	1	1	2	2	3	4
Emerging	-	-	-	-	0	1	5	10	16	19	32	55	78	114	171
Advanced	496	490	492	505	540	602	623	664	698	695	751	805	858	899	952

Source: International Federation of Robotics, authors' calculations

Table 1 reports the average annual growth rate of the number of multipurpose industrial robots by country group and sector.[14] The growth in the number of robots in this period was around 6 per cent annually, with larger growth rates observed in primary industries and manufacturing. With respect to country groups, we find that the largest growth in the stock of robots was registered in emerging and in transition economies. These high growth rates are also a result of

[14] These figures calculate the number of robots by group of countries and industries from which the growth rate is derived.

the low number of robots in the initial years. Again, the growth rates in manufacturing and primary industries are above average in most cases (with the exception of the emerging economies).

Table 1: Average annual growth of the stock of industrial robots, 2000-2014

Industry Description	World	Advanced	Emerging	Transition	Other
Primary	7.6%	6.7%	61.9%	34.7%	42.1%
Manufacturing	6.2%	4.7%	67.3%	52.6%	24.6%
Robotized Services	2.6%	1.0%	68.5%	32.6%	10.0%
Total	6.2%	4.7%	67.3%	50.9%	24.3%

Note: Primary includes agriculture, fishing, forestry and mining. Robotized services include electricity and water supply (DtE), construction (F) and scientific research and development; other professional, scientific and technical activities; veterinary activities; education (MtN&P).
Source: WIOD; own calculations.

3.3. Growth of other main variables

The main question addressed here is how the use of robots has impacted on the growth performance of industries and countries with a focus on employment and value added growth. The next two tables show average growth rates of employment and real value added to provide some indication of the developments.

Specifically, Table 2 presents the average annual growth of persons employed by country and industry group. The general pattern for the world as a whole is that employment has been growing in almost all industries except for the primary sector. On average, employment growth has been at 1.7 per cent over this period. Positive employment growth is also recorded for all country groups. It is only for the transition economies that we observe total job losses with an average annual rate of 0.1 per cent.[15] Particularly strong employment growth of 2.2% is seen in the emerging economies.

[15] These countries also faced difficult macro-economic situations over the period considered.

Table 2: Average annual growth of industrial employment in %, 2000-2014

Industry Description	World	Advanced	Emerging	Transition	Rest
Primary	-0.7%	-1.2%	-0.6%	-3.3%	-3.3%
Manufacturing	2.1%	-1.5%	3.3%	-1.7%	0.3%
Robotized Services	3.1%	0.5%	4.2%	0.5%	1.2%
Non-robotized Services	3.0%	0.9%	4.5%	1.8%	1.5%
Total	1.7%	0.4%	2.2%	-0.1%	0.7%

Note: Primary includes agriculture, fishing, forestry and mining. Robotized services include electricity and water supply (DtE), construction (F) and scientific research and development; other professional, scientific and technical activities; veterinary activities; education (MtN&P).
Source: WIOD; own calculations.

Some negative growth rates are also observed in the manufacturing industries of advanced and transition economies. The positive growth rates of employment in services in advanced economies are lower than the growth rates of job losses in the manufacturing and primary sectors. The total employment growth rate in advanced economies is, however, still positive because of the larger share of employment in the services sector. By contrast, emerging economies and the group rest of the countries managed to generate a large amount of jobs in both the manufacturing and services sectors. Employment in manufacturing and services has been growing in emerging economies by an annual average rate of 3.3 per cent and 4.3 per cent, respectively.

Table 3: Average annual growth rate of real value added in %, 2000-2014

Industry Description	World	Advanced	Emerging	Transition	Rest
Primary	2.1%	1.3%	2.8%	1.9%	-0.2%
Manufacturing	3.1%	0.8%	9.3%	2.7%	4.3%
Robotized Services	1.4%	0.1%	6.0%	1.8%	1.1%
Non-robotized Services	2.3%	1.5%	6.1%	4.0%	2.4%
Total	2.3%	1.2%	6.2%	3.2%	2.5%

Note: Primary includes agriculture, fishing, forestry and mining. Robotized services include electricity and water supply (DtE), construction (F) and scientific research and development; other professional, scientific and technical activities; veterinary activities; education (MtN&P).
Source: WIOD; own calculations.

Table 3 reports growth rates of real value added (in constant 2010 US dollars) by country and industry group. Globally, real value added has been growing at 2.3 per cent on average. The total growth rates in non-advanced economies have generally been higher. Overall, real value added increased in all industries and country groups; particularly high growth rates (in relative terms) were observed in the manufacturing sector of non-advanced countries.

3.4. Selected descriptive evidence

In the following, a framework is developed to examine the impacts of the rise in the number of robots and of TFP on employment and real value added and other related indicators (hours worked, nominal value added and the share of labour income in value added). Before we do so, it is useful to look at the relationship between these main outcome variables, i.e. employment growth and real value added growth, and the stock of robots with the help of simple contemporaneous correlations. In addition, to facilitate a comparison, the same relationships are shown for TFP. Since the econometric model will use a much more refined industry disaggregation, correlations for these more disaggregated industries are established as well, combining primary, manufacturing as well as robotized and non-robotized services industries.

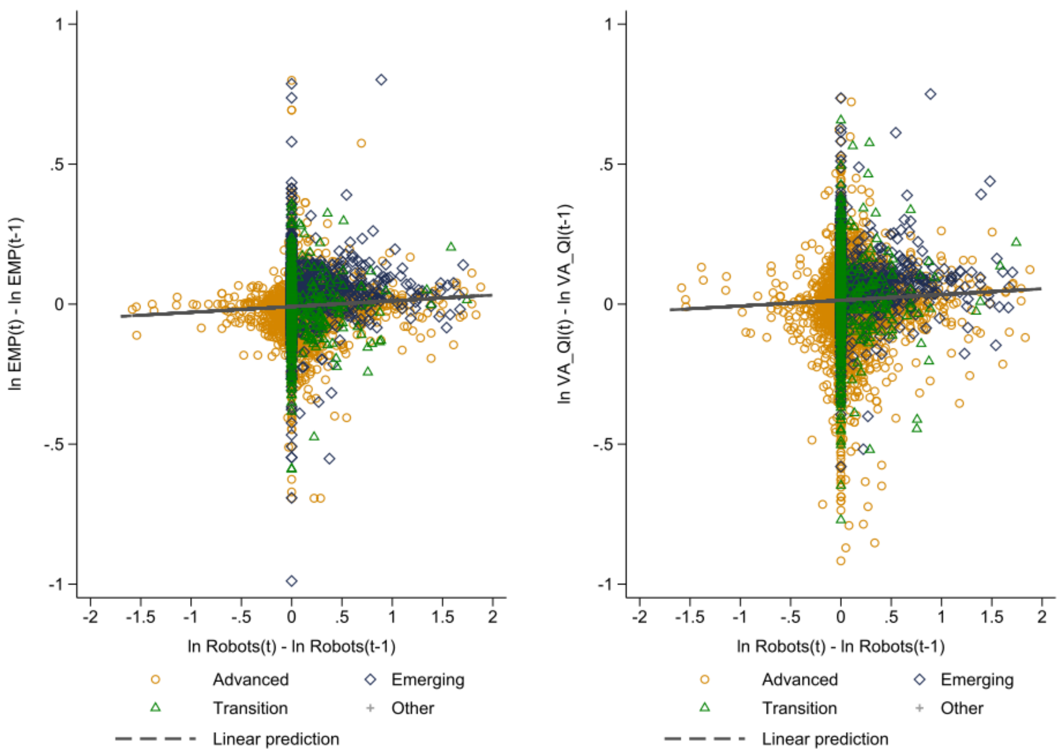
Starting with the correlation between the rise in the stock of robots and employment (Figure 3, panel a), we arrive at a surprising result. The simple correlation between the two growth rates suggests that industries that expand their robot stock more quickly are also those that have higher employment growth. Given the aforementioned concerns about the negative impacts of automation (and digitalization) on employment, this positive correlation conveys a more optimistic message. It should be mentioned though that this exercise is only a first superficial investigation of the data and only captures the 'direct' effect of the robotization of industries. Moreover, any lagged effects are disregarded. These issues will be dealt with in the econometric model.

One interesting factor is the large number of observations with zero growth of robots. These are mainly for the non-robotized services industries which do not use industrial robots.

The result for the correlation between the rise in the stock of robots and real value added growth (Figure 3, panel b) was to be expected. A higher growth rate of the stock of robots goes hand in hand with higher real value added growth which the newly installed robots should translate into cost savings, lower prices and nominal output. This positive effect on real value added growth potentially counteracts the assumed labour-saving nature of the installation of the new technologies (e.g. robots) and might explain the aforementioned positive correlation with employment growth. Nonetheless, this relationship warrants a more thorough analysis which will be provided in the econometric section.

Figure 3: Correlations between main outcome variables and the increase in the stock of robots, global, 2000-2014

(a) employment growth ***(b) real value added growth***



Note: Contemporaneous correlations. The graphs only show observations with log growth rates of employment and real value added greater or equal to -1 and smaller or equal to 1 and log growth rates of robot stocks greater or equal to -2 and smaller or equal to 2. The linear prediction is obtained using all observations.
Source: WIOD Version 2016 (Socio-Economic Accounts), International Federation of Robotics IFR) database, authors' own calculations.

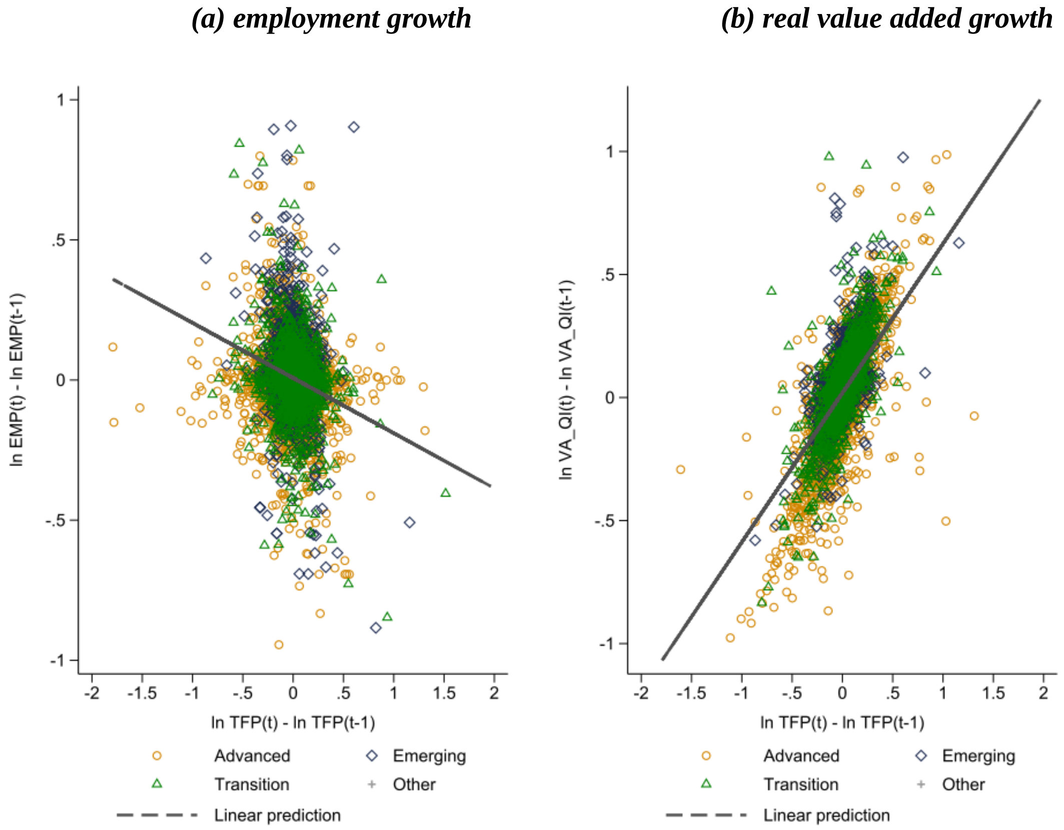
Finally, Figure 3 also confirms the assertion made above that the growth rate of robot stocks is generally higher in emerging and transition economies than in advanced countries. This can partly be explained by the base effect, which reflects that the marginal impact of an additional robot can be expected to be higher when the stock of robots is still low. With a view to the choice of functional form, it is therefore sensible to estimate the model in (log) growth rates[16].

Remaining at the global level but replacing the increase in the robot stock with TFP growth delivers some additional insights. While the relationship between the growth of both TFP and of real value added is again positive (Figure 4, panel b), and very strongly so, the relationship in the case of employment is negative (Figure 4, panel a). This is the expected result, at least if

[16] Alternatives would be to estimate the model in levels of first differences.

technological progress is labour saving[17]. This is an important marker for the purpose of this paper, namely that the growth of the stock of robots reflects a very specific and clearly only part of the technological progress.

Figure 4: Correlations between main outcome variables and TFP growth, global, 2000-2014



Note: Contemporaneous correlations. The graphs only show observations with log growth rates of employment and real value added greater or equal to -1 and smaller or equal to 1 and log TFP growth greater or equal to -2 and smaller or equal to 2. The linear prediction is obtained using all observations.

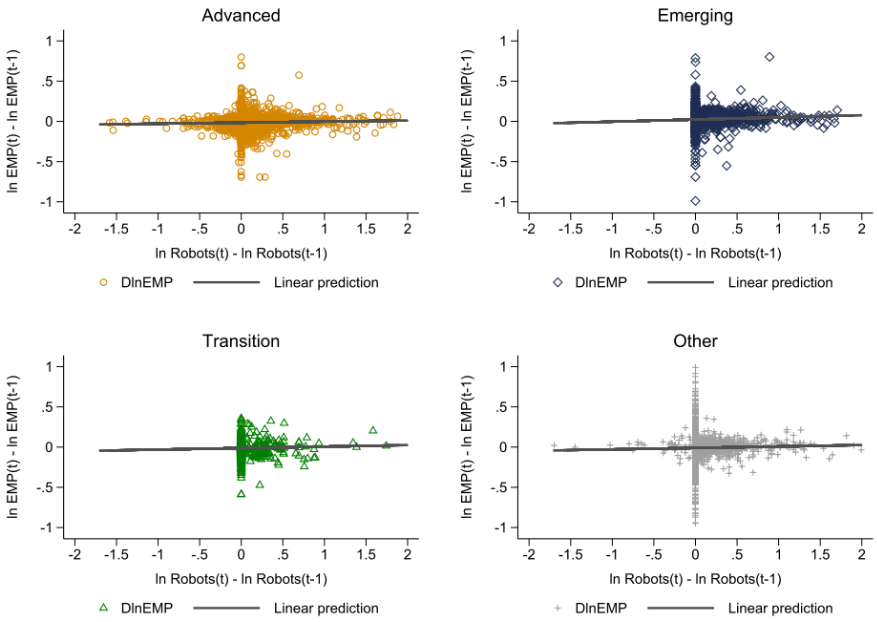
Source: WIOD Version 2016 (Socio-Economic Accounts), authors' own calculations.

Another important, albeit preliminary, insight that can be gained from the relationships between the growth of employment and real value added and the increase in the stock of robots is the degree of country group homogeneity or heterogeneity in terms of this relationship. These can provide some initial guidance as to whether it is practical to estimate these relationships for the global sample.

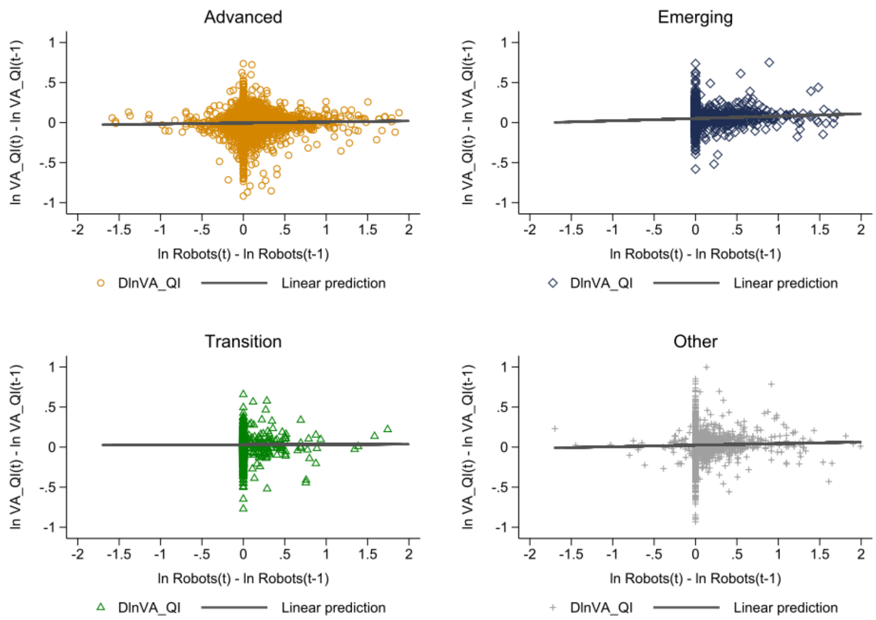
[17] This negative relationship between the growth of both TFP and employment emerges from the logic of growth accounting and is therefore spurious, as TFP growth is calculated as the residual between real value added growth and the growth of factor inputs.

Figure 5: Correlations between main outcome variables and the increase in the stock of robots, by country group, 2000-2014

(a) employment growth



(b) real value added growth



Note: Contemporaneous correlations. The graphs only show observations with log growth rates of employment and real value added greater or equal to -1 and smaller or equal to 1 and log growth rates of robot stocks greater or equal to -2 and smaller or equal to 2. The linear prediction is obtained using all observations.

Source: WIOD Version 2016 (Socio-Economic Accounts), International Federation of Robotics IFR) database, authors' own calculations.

To this end, panel a of Figure 5 shows individual scatter plots and the associated linear predictions for the four country groups. First and foremost, it is noteworthy that all slopes are positive. While the slope of the linear regression line is steeper for the emerging and slightly steeper for the transition economies compared to the advanced economies, the differences are not statistically significant. When interacting, the effect of the increase in the stock of robots with dummy group variables, no statistically significant differences in the slopes are identified. The same holds true for the relationships between real value added growth and the rise in the stock of robots, i.e. no statistically significant differences in the slopes of the regression lines can be detected (Figure 5, panel b). The choice of estimating the effects of the growth of the stock of robots on employment and value added for the global sample seems appropriate.

4. Methodology

As mentioned above, this paper applies and adapts the econometric framework based on Autor and Salomons (2018) (AS) to investigate the impact of the changes in the stock of industrial multipurpose robots and TFP growth on important indicators at the industry level based on the data described in Section 3.

4.1. Econometric model

The applied econometric model draws on the framework developed by AS and uses total factor productivity (TFP) growth as a catch-all proxy for automation and technological progress. Apart from being readily available for a sufficient number of advanced countries, on key advantage of the TFP measure is that it is theoretically akin to, and empirically strongly related to, technological change. The downside is that TFP is a residual value, derived as the difference between changes in factor inputs and the change in output. Hence, it is unclear what the residual actually captures and it is only relatively loosely related to the introduction of new technologies or a new industrial revolution.

One particularly interesting feature of the AS framework is that it does not only capture the direct effect of TFP growth but also takes backward and forward linkages into account. This is important because if an industry becomes more productive, e.g. by automating a particular sequence of the production process, the downstream industries might also benefit in the form of lower prices (resulting in positive forward linkages). Likewise, suppliers in upstream industries might benefit if the productivity rise in the automated industry leads to an expansion of that industry and higher demand for inputs from the upstream industry as a consequence (resulting in positive backward linkages). Since the time lags of all potential impacts of technological progress are uncertain, the AS model includes up to five lagged values in addition to the contemporaneous value of TFP growth. The overall impact is calculated as the sum of the estimated contemporaneous and lagged effects.

This paper extends the AS model in three important ways. First, the focus of the analysis is extended to emerging and transition countries, while AS focusses on several advanced economies. To ensure a cross-country variation that can be econometrically generalized for the world economy, our model includes emerging and transition economies along with advanced economies as available from the WIOD (see Appendix Table A.1).

Second, this paper uses the change in the stock of industrial robots (R) at the country-industry level as another proxy for technological change in addition to TFP growth. As mentioned in the introduction, industrial robots are considered a very narrow measure for technological change. Nevertheless, in comparison to TFP growth (which is the indicator used by AS), robots are more closely related to the introduction of disruptive technologies related to Industry 4.0.

Third, the econometric model allows for an open economy setting in the sense that the indirect effects of industrial robots on labour market outcomes and value added also include linkages to industries of foreign countries along the GVC[18]. Therefore, international linkages (indicated by the superscript int) are taken into account in addition to the domestic linkages (indicated by a superscript dom).

Following the framework of AS, the model includes not only the contemporaneous effects of robots, but also lagged effects. However, with respect to the time dimension of the WIOD data, the lags are limited to three periods[19]. The entire model is specified in logarithmic forms, including the linkages terms, so that for the outcome variables on the left hand side, growth rates are obtained as the difference in logs.

The baseline specification of the econometric model takes the following form:

[18] See Nishioka and Ripoll (2012) for a similar approach studying R&D spillovers.

[19] This is shorter than the 5-year lags used in AS, which is due to the much shorter sample period available for this exercise.

$$\Delta lnY_{cit} = \beta_0 + \sum_{k=0}^{3} \beta_1^k \Delta lnR_{ci,t-k} + \sum_{k=0}^{3} \beta_2^k \Delta lnR_{ci,t-k}^{dom-BW} + \sum_{k=0}^{3} \beta_3^k \Delta lnR_{ci,t-k}^{dom-FW}$$
$$+ \sum_{k=0}^{3} \beta_4^k \Delta lnR_{ci,t-k}^{int-BW} + \sum_{k=0}^{3} \beta_5^k \Delta lnR_{ci,t-k}^{int-FW} + \mu_{ct} + \mu_i + \varepsilon_{ict}, \qquad (2)$$

$$Y \in \{EMP, HEMP, LSH, VA^{real}, VA^{nominal}\}$$

where ΔlnY_{cit} is the log growth of the dependent variable of interest in industry i in country c at time t which could either be employment (EMP) growth, growth in hours worked ($HEMP$), labour share in value added (LSH) growth, real valued added (VA^{real}) growth and nominal value added ($VA^{nominal}$) growth.

There are five sets of explanatory variables: ΔlnR_{cit} indicates the growth of the stock of industrial multipurpose robots in country c and in industry i at time t. The time lags are indexed by k which runs from 0 to 3, with $k = 0$ being the contemporaneous value of the variable.

There are four other variables that are indicators of the stock of robots along the backward and forward linkages, both in domestic and in international economies. $\Delta lnR_{cit}^{dom-BW}$ is the accumulated growth in the stock of robots along the domestic backward linkages (i.e. suppliers) to industry i in country c at time t, excluding the own industry i's contribution. $\Delta lnR_{cit}^{dom-FW}$ is the accumulated growth in the stock of robots along the domestic forward linkages (i.e. customers) to industry i in country c at time t, excluding the own industry i's contribution. $\Delta lnR_{cit}^{int-BW}$ is the accumulated growth in the stock of robots along the international backward linkages to industry i in country c at time t, excluding the own country c's contribution. $\Delta lnR_{cit}^{int-FW}$ is the accumulated growth in the stock of robots along the international forward linkages to industry i in country c at time t, excluding the own country c's contribution. Given that three lagged values are included, each set of these explanatory variables includes four terms. The estimated coefficients of each of these sets are added together to give the estimated effect of the variable in Equation (2). The statistical significance of the summed effect of the contemporaneous and lags of each explanatory variable is based on the F-test for the joint significance of the four estimates.

The definition of the domestic backward ($\Delta lnR_{cit}^{dom-BW}$) and forward linkages ($\Delta lnR_{cit}^{dom-FW}$) makes use of the standard input-output methodology to define the relevant production linkages. In essence, they are the weighted averages of the log changes in robots in the downstream and upstream industries. The weights reflect the domestic direct and indirect production linkages as recorded in the inter-country input-output tables. That is, the submatrix of the global Leontief inverse and the submatrix of the global Ghosh inverse correspond to the inter-industry linkages within the domestic economy of each country. Hence, the weights are the 'domestic' input-output coefficients of the Leontief inverse (with the typical element $l_{j,i}$) in the case of backward linkages[20] and the coefficient of the Ghosh inverse (with the typical element $g_{i,j}$) for forward linkages. This yields the following definition of the domestic linkages

$$\Delta lnR_{c,i,t}^{dom-BW} = \sum_{j(j\neq i)}^{J} l_{(cj,ci),t} \times \Delta lnR_{c,j,t}$$

$$\Delta lnR_{c,i,t}^{dom-FW} = \sum_{j(j\neq i)}^{J} g_{(ci,cj),t} \times \Delta lnR_{c,j,t} \tag{3}$$

The subscript $j \neq i$ in the coefficient of the Leontief and Ghosh coefficient indicates that the linkages term excludes the within-industry linkages for a given industry i as mentioned above, where J denotes the total number of industries.

The international production linkages are defined analogously, only that in this case, both the intra-industry and cross-country linkages within the GVCs are included, as these do not constitute within-industry linkages in the same country. Assigning index f to the foreign countries with which the international linkages have been established and with the total number of countries F, they are defined as follows:

$$\Delta lnR_{c,i,t}^{int-BW} = \sum_{j=1}^{J} \sum_{f(f\neq c)}^{F} l_{(fj,ci),t} \times \Delta lnR_{f,j,t}$$

$$\Delta lnR_{c,i,t}^{int-FW} = \sum_{j=1}^{J} \sum_{f(f\neq c)}^{F} g_{(ci,fj),t} \times \Delta lnR_{f,j,t} \tag{4}$$

The term $\Delta lnR_{f,j,t}$ indicates the log change in the stock of robots in industry *j* of a foreign country *f* in year *t*. The typical element of the Leontief inverse, $l_{(fj,ci),t}$, indicates the purchases of industry *i* in country *c* from foreign country *f*'s industry *j* at time *t*. Note that the purchases of industry *i* in

[20] In the context of all linkages terms, the *first* industry index indicates the *selling* industry and the *second* one denotes the *buying* industry following the convention in input-output modelling. In the case of backward linkages, the usual labelling of indices in the input-output literature is reversed in order to stick to the general notation that *i* indicates the industry under consideration.

country c from all foreign industry i's are included here[21]. Likewise, the typical element of the Ghosh inverse, $g_{(ci,fj),t}$ indicates the sales of industry *i* in country *c* to foreign country *f*'s industry *j* at time *t*.

In Equation (2), we include country-time- μ_{ct} and industry- μ_i fixed effects (FEs). While the latter controls for global technological progress within each industry, the former controls for macro business cycles in each country. The remaining impacts estimated by β parameters in Equation (2) are mainly the changes within industry-country pair variables over time. Note that this is a more detailed control for fixed effects than in AS, which used a broader aggregation of sectors than the latter FEs. This model therefore reduces the endogeneity due to the omitted variable bias to the minimum possible. ε_{ict} denotes the error term. To control for heteroscedasticity in the structure of error term, error terms are clustered by each country-industry pairs μ_{ci}, which controls for the shocks in the dependant variable of each country-industry pair over time that are not due to the explanatory variables.

As mentioned above, the impacts of TFP growth ($\Delta lnTFP$) are also taken into account. Otherwise, the estimations on robot variables might suffer from the omitted variable bias. In other words, by including TFP variables, we control for any other possible form of technological progress apart from industrial robots. For the construction of the TFP growth of industries, the same procedure as for robots growth is used. For example, $\Delta lnTFP_{cit}^{int-BW}$ indicates the log TFP growth accumulated in international backward linkages of industry i in country c to all industries in foreign countries analogous to the respective variable on the growth of the stock of robots as follows:

$$\Delta lnTFP_{c,i,t}^{int-BW} = \sum_{j=1}^{J} \sum_{f(f\neq c)}^{F} l_{(fj,ci),t} \times \Delta lnTFP_{f,j,t} \tag{5}$$

While linkages variables on TFP growth are constructed similarly to those on robots growth, the direct effect of TFP growth contains one particular feature. Since a country's own TFP growth entails a mechanic negative relationship to employment as shown below, the own (industry-country level) TFP growth is replaced with the average of foreign countries' TFP growth in the respective industry. This is indicated with an asterisk in the superscript of the log growth of TFP, i.e. $\Delta lnTFP_{cit}^{*}$. It is important to note that for advanced countries this variable is calculated using the average TFP growth of all advanced countries other than the one under question, whereas for

[21] The reason is that, say, a purchase by the Chinese steel industry from the Indian steel industry is an inter-industry transaction.

all other countries, this variable is calculated using the average TFP growth of all non-advanced economies other than the one under question in a given industry. Considering that Φ^{A} is the set of advanced economies reported in Appendix Table A 1, and $\Phi^{\mathrm{A}'}$ is the set of all other countries reported in that table, $\Delta lnTFP^{*}_{cit}$ is defined as follows:

$$\Delta lnTFP^{*}_{cit} = \frac{\sum_{f \neq c}^{F^X - 1} \Delta lnTFP_{fit}}{F^X - 1}, \qquad f \in \Phi^X \ \wedge \ X \in \{A\,, A'\} \tag{6}$$

where F^A and $F^{A'}$ are the total numbers of advanced and non-advanced economies, respectively.

The full model, including the TFP growth rate, takes the following form:

$$\begin{aligned} \Delta lnY_{cit} = \ & \beta_0 + \sum_{k=0}^{3} \beta_1^k \Delta lnR_{ci,t-k} + \sum_{k=0}^{3} \beta_2^k \Delta lnR_{ci,t-k}^{dom-BW} + \sum_{k=0}^{3} \beta_3^k \Delta lnR_{ci,t-k}^{dom-FW} \\ & + \sum_{k=0}^{3} \beta_4^k \Delta lnR_{ci,t-k}^{int-BW} + \sum_{k=0}^{3} \beta_5^k \Delta lnR_{ci,t-k}^{int-FW} + \sum_{k=0}^{3} \beta_6^k \Delta lnTFP_{ci,t-k}^{*} \\ & + \sum_{k=0}^{3} \beta_7^k \Delta lnTFP_{ci,t-k}^{dom-BW} + \sum_{k=0}^{3} \beta_8^k \Delta lnTFP_{ci,t-k}^{dom-FW} \\ & + \sum_{k=0}^{3} \beta_9^k \Delta lnTFP_{ci,t-k}^{int-BW} + \sum_{k=0}^{3} \beta_{10}^k \Delta lnTFP_{ci,t-k}^{int-FW} + \mu_{ct} + \mu_i + \varepsilon_{ict}, \\ & Y \in \left\{EMP, HEMP, LSH, VA^{real}, VA^{nominal}\right\} \end{aligned} \tag{7}$$

This model features ten sets of distributed lagged explanatory variables, each one featuring the contemporary value of the variable up to three lags, in addition to country-time- and industry FEs.

5. Results and discussion

5.1. Estimation results

5.1.1. Benchmark results

As mentioned above, the model used in this paper departs from the model applied in AS in various respects. Therefore, as a prelude, we test whether the results of AS can be reproduced with the data used in this paper. The sample of countries in our dataset is limited to only those used in AS; the important difference is that the time period is much shorter (2000-2014).

Methodologically, the model only includes the direct and indirect effects of TFP growth (the effects of robots are examined later). The reported specification follows AS by including five distributed lagged values for each of the explanatory variables. Additionally, these regressions are weighted by employment shares or value added shares as in AS. Further fixed effects for groups of industries (as in AS) are used. Departing from AS, however, international linkages—which are absent in the AS specification—are included. The estimated model takes the following form:

$$\begin{aligned} \Delta lnY_{cit} = \ & \beta_0 + \sum_{k=0}^{5} \beta_6^k \Delta lnTFP^{*}_{ci,t-k} + \sum_{k=0}^{5} \beta_7^k \Delta lnTFP^{dom-BW}_{ci,t-k} \\ & + \sum_{k=0}^{5} \beta_8^k \Delta lnTFP^{dom-FW}_{ci,t-k} + \sum_{k=0}^{5} \beta_9^k \Delta lnTFP^{int-BW}_{ci,t-k} \\ & + \sum_{k=0}^{5} \beta_{10}^k \Delta lnTFP^{int-FW}_{ci,t-k} + \mu_{ct} + \mu_s + \varepsilon_{ict}, \end{aligned} \tag{8}$$

$$Y \in \{EMP, HEMP, LSH, VA^{real}, VA^{nominal}\}$$

where μ_s is the aggregate sector FE as defined by AS, and the distributed lags of variables include the contemporaneous and five lags of the explanatory variables.

Table 4 shows that the results reported by AS for the period 1970-2007 (Table 8 in AS) or the period 2000-2015 (Table 6 in AS) are by and large reproduced with the data constructed in this model – at least qualitatively, though not quantitatively. For example, the direct effect of TFP growth on employment growth (column 1) is estimated to be -0.39 compared to -0.95 in AS. The coefficient for the domestic backward linkages is also smaller in scope, but positive, as in AS, while the domestic forward linkages are not statistically significant as is the case in AS[22]. These results are robust and consistent, even if we exclude international linkages. The direct impact of TFP growth on value added variables is statistically insignificant; as for the similar period in Table 6 of AS, these two variables are also statistically insignificant.

Table 4: Estimated effects of TFP growth in the benchmark specification (selected countries)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$\Delta \ln \boldsymbol{EMP_{cit}}$	$\Delta \ln \boldsymbol{HEMP_{cit}}$	$\Delta \ln \boldsymbol{LSH_{cit}}$	$\Delta \ln \boldsymbol{VA_{cit}^{real}}$	$\Delta \ln \boldsymbol{VA_{cit}^{nominal}}$
$\sum_{k=0}^{5} \boldsymbol{\beta_6^k \Delta lnTFP_{ci,t-k}^{*}}$	-.39***	-.34***	.092	.095	.022
F-Test of joint significance	(0)	(0)	(.767)	(.434)	(.831)
$\sum_{k=0}^{5} \boldsymbol{\beta_7^k \Delta lnTFP_{ci,t-k}^{dom-BW}}$	.708***	.869**	.148	.467	.627*
F-Test of joint significance	(.008)	(.021)	(.65)	(.156)	(.085)
$\sum_{k=0}^{5} \boldsymbol{\beta_9^k \Delta lnTFP_{ci,t-k}^{int-BW}}$	-.903**	-1.176***	-.126	.327	-1.529***
F-Test of joint significance	(.011)	(.003)	(.795)	(.673)	(.001)
$\sum_{k=0}^{5} \boldsymbol{\beta_8^k \Delta lnTFP_{ci,t-k}^{dom-FW}}$	.03	.017	-.375*	-.103	.433*
F-Test of joint significance	(.742)	(.89)	(.068)	(.517)	(.097)
$\sum_{k=0}^{5} \boldsymbol{\beta_{10}^k \Delta lnTFP_{ci,t-k}^{int-FW}}$	1.011***	1.093**	-.28	.615	2.251***
F-test of joint significance	(.002)	(.017)	(.441)	(.207)	(0)
Weight	Employment	Hours worked	Value added	Value added	Value added
R-sq.	.328	.35	.15	.242	.289
Obs	8036	8036	8036	8036	8036

Note: The sample includes the same countries as in AS (2018). P values for the F-test of joint significance ($\beta^0 + \beta^1 + \beta^2 + \beta^3 = 0$) in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. The size of the coefficients is obtained by summing up the estimated coefficients of the contemporaneous values and the five lagged values. All specifications include country-time fixed effects and *sector* fixed effects. Estimated with STATA using the *reghdfe* estimation command.

However, when estimating the same model with the full sample of countries in our data and all available industries (including agriculture and services), using only three distributed lags instead of five and including industry instead of sector group FEs[23], the majority of the statistically significant coefficients disappear (Table 5). Therefore, the results do not appear to be particularly

[22] In contrast to AS, the variables are not normalized. In fact, there is no real need to normalize as a linear model is estimated.

[23] This is done to reduce the omitted variable bias.

robust in these respects. Many other robust checks point in that direction and it can therefore be concluded from these checks that country samples matter.

Table 5: Estimated effects of TFP growth (all countries)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$\Delta \ln EMP_{cit}$	$\Delta \ln HEMP_{cit}$	$\Delta \ln LSH_{cit}$	$\Delta \ln VA_{cit}^{real}$	$\Delta \ln VA_{cit}^{nominal}$
$\sum_{k=0}^{3} \beta_6^k \Delta lnTFP_{ci,t-k}^{*}$	.087	.076	-.066	.121*	.163***
F-Test of joint significance	(.167)	(.258)	(.284)	(.057)	(.008)
$\sum_{k=0}^{3} \beta_7^k \Delta lnTFP_{ci,t-k}^{dom-BW}$	.123	.235**	-.009	.238*	.209*
F-Test of joint significance	(.205)	(.037)	(.923)	(.05)	(.095)
$\sum_{k=0}^{3} \beta_9^k \Delta lnTFP_{ci,t-k}^{int-BW}$	.204	.293	-.475**	.909***	.37*
F-Test of joint significance	(.247)	(.114)	(.015)	(.001)	(.095)
$\sum_{k=0}^{3} \beta_8^k \Delta lnTFP_{ci,t-k}^{dom-FW}$	-.009	-.014	.004	-.152*	-.021
F-Test of joint significance	(.876)	(.817)	(.934)	(.072)	(.807)
$\sum_{k=0}^{3} \beta_{10}^k \Delta lnTFP_{ci,t-k}^{int-FW}$	.386***	.434***	-.375*	.647***	1.277***
F-test of joint significance	(.005)	(.004)	(.069)	(.006)	(0)
R-sq.	0.118	0.135	0.079	0.174	0.246
Obs	20,609	20,191	20,609	20,609	20,609

Note: The sample includes all WIOD countries. P values for the F-test of joint significance ($\beta^0 + \beta^1 + \beta^2 + \beta^3 = 0$) in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. The size of the coefficients is obtained by summing up the estimated coefficients of the contemporaneous values and the three lagged values. All specifications include country-time fixed effects and industry fixed effects. Regressions are unweighted. Estimated with STATA using the *reghdfe* estimation command.

The direct effects of TFP growth on labour market outcomes, in particular, are no longer statistically significant. Only the corresponding effect on nominal value added remains statistically significant at the 5 per cent level, with that on real value added at the 10 per cent level. The domestic linkages effects on labour market outcomes show only modest impacts, with the coefficient of the domestic backward linkages being the only positive and statistically significant one – and only when employment is measured in hours worked. As regards international linkages, it is suggested that international forward linkages foster employment. In contrast to the above, real and nominal value added growth is positively affected by own-industry TFP growth, backward linkages—both domestic and international—and international forward linkages.

These results suggest that international linkages matter. The reasoning behind this is that a given industry, say, the machinery industry in Romania, may benefit from TFP growth in foreign supplier industries in terms of additional value added growth. In fact, a 1 percentage point increase in the TFP growth rate of the supplying industry results in a growth rate of real value added that is around 0.9 per cent higher. A similar interpretation, albeit with a smaller percentage point increase of 0.65, holds for foreign customer industries across the forward international linkages of a given industry.

5.1.2. Taking robots into account

The main motivation for this paper, however, is to assess the impact of robots on the growth of employment and value added (and other variables). Thus, together with TFP growth (which is a rather broad measure of technology), the growth in the stock of robots is included as shown in Equation (7). This enhanced model includes the growth of robots and TFP as explanatory variables together with the associated linkages terms. The estimation results are presented in Table 6.

The results suggest that there is a positive and statistically significant direct effect of TFP growth for real and nominal value added only. No such effect is found for employment growth variables. The TFP growth of suppliers along the domestic backward linkages stimulates value added outcomes, and along international backward linkages for real value added growth. Domestic forward linkages do not significantly impact the growth of the variables considered. However, forward international linkages are large and significantly positive.

Turning to the effects arising from the growth in installed robots, the upper part of Table 6 suggests a mildly significant and positive direct effect on employment (an increase by 0.011 percentage points). A similar effect is found for the growth in hours worked. An even higher significant positive effect is also found for real value added growth (0.023 percentage points), but less so in nominal terms (0.009 per cent). With respect to the labour share, no statistically significant direct effect is found.

Table 6: Estimated effects of the growth of robots and TFP

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$\Delta \ln EMP_{cit}$	$\Delta \ln HEMP_{cit}$	$\Delta \ln LSH_{cit}$	$\Delta \ln VA_{cit}^{real}$	$\Delta \ln VA_{cit}^{nominal}$
Growth of robots					
$\sum_{k=0}^{3} \boldsymbol{\beta_1^k \Delta lnR_{ci,t-k}}$	.011***	.01***	-.001	.023***	.009**
F-test of joint significance	(.001)	(.003)	(.67)	(0)	(.031)
$\sum_{k=0}^{3} \boldsymbol{\beta_2^k \Delta lnR_{ci,t-k}^{dom-BW}}$	.024	.053*	.021	.007	.017
F-test of joint significance	(.239)	(.051)	(.237)	(.801)	(.456)
$\sum_{k=0}^{3} \boldsymbol{\beta_3^k \Delta lnR_{ci,t-k}^{int-BW}}$	.055	.095**	-.064	.044	.19***
F-test of joint significance	(.157)	(.022)	(.101)	(.478)	(0)
$\sum_{k=0}^{3} \boldsymbol{\beta_4^k \Delta lnR_{ci,t-k}^{dom-FW}}$	-.027*	-.037*	.016	-.039	-.054**
F-test of joint significance	(.098)	(.079)	(.326)	(.173)	(.039)
$\sum_{k=0}^{3} \boldsymbol{\beta_5^k \Delta lnR_{ci,t-k}^{int-FW}}$	.037	.047	.083***	.1***	-.041
F-test of joint significance	(.219)	(.122)	(.005)	(.006)	(.199)
TFP growth					
$\sum_{k=0}^{3} \boldsymbol{\beta_6^k \Delta lnTFP^{*}_{ci,t-k}}$	.088	.072	-.087	.141**	.188***
F-Test of joint significance	(.19)	(.314)	(.178)	(.028)	(.002)
$\sum_{k=0}^{3} \boldsymbol{\beta_7^k \Delta lnTFP_{ci,t-k}^{dom-BW}}$	.178	.334**	-.032	.47***	.374**
F-test of joint significance	(.149)	(.016)	(.778)	(.001)	(.014)
$\sum_{k=0}^{3} \boldsymbol{\beta_9^k \Delta lnTFP_{ci,t-k}^{int-BW}}$	.266	.353*	-.373*	.991***	.358
F-test of joint significance	(.179)	(.086)	(.083)	(.001)	(.15)
$\sum_{k=0}^{3} \boldsymbol{\beta_8^k \Delta lnTFP_{ci,t-k}^{dom-FW}}$	.061	.11	-.008	-.152	.036
F-test of joint significance	(.405)	(.126)	(.927)	(.156)	-0.685
$\sum_{k=0}^{3} \boldsymbol{\beta_{10}^k \Delta lnTFP_{ci,t-k}^{int-FW}}$	.252	.293*	-.4*	.605**	1.254***
F-test of joint significance	(.123)	(.078)	(.082)	(.015)	(0)
R-sq.	.123	.139	.08	.187	.261
Obs	19500	19092	19500	19500	19500

Note: The sample includes all WIOD countries. Robust standard errors are clustered by country-industry pairs in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. We report P values for the F-test $\beta^0+\beta^1+\beta^2+\beta^3=0$. The size of the coefficients is obtained by summing up the estimated coefficients of the contemporaneous values and the three lagged values. All specifications include country-time fixed effects and industry fixed effects. Regressions are unweighted. Estimated with STATA using the *reghdfe* estimation command.

This result might deserve careful consideration, although it generally confirms the descriptive results shown above. One possible explanation for this is that it can be assumed that robots are introduced when firms become more profitable. This should lead to lower unit costs and lower prices in a competitive environment. Assuming that consumers react sensitively to such price changes, demand for these products increases (thus having a positive impact on value-added growth), which (depending on elasticities across the factors of production) may therefore also result in higher employment (despite the labour-saving nature of robots). If the production function is close to a Cobb-Douglas (i.e. substitution elasticity of 1 between factors of production), the labour share remains unchanged. Some further theoretical arguments are summarized in Box 1.

Box 1: Theoretical arguments

When considering a change in productivity or an increase in capital in simple (neoclassical) model frameworks, similar outcomes can be expected (though one must bear in mind that these rest on a full employment assumption). For example, in a simple (standard) Ricardo-Viner model (specific factors model), the increase in capital (or productivity) would shift employment into this industry. The increase in capital (or productivity) in an industry increases the marginal productivity of labour which—at given goods prices—even increases (real) wages in that industry. One might argue that the purpose of the use of robots could be more industry-specific than TFP growth, which might explain the significant impact of robots on employment at the industry level. Similarly, in a Heckscher-Ohlin framework (i.e. with capital mobile across industries), an increase in capital would shift employment to capital-intensive industries.

In addition, old vintages of machineries could also be replaced and upgraded by newer machineries (or robots) as a form of process innovation[24]. In many cases, when firms upgrade their production processes, they also change their products, resulting in product innovation and/or more diversification, whose net effect might be unclear.

Another argument is that the industrial robots effect employed tasks within each industry differently. For instance, Sachs and Kotlikof (2012) and Benzel et al. (2015) argue that smart machines are replacing unskilled labour while complementing skilled labour. Such a capital-skill complementarity would imply that a higher capital stock would increase demand for qualified labour and reduce that for unqualified labour (ceteris paribus); thus, the net effect of changes in capital intensity on total employment is unclear and depends on all substitution elasticities across production factors.

These are potential explanations as to why our econometric results indicate that the aggregate employment effect of installing new machinery (robots) is (slightly) positive (controlling for TFP growth).

With regard to linkages, the effect of the stock of robots along the domestic backward linkages is positive for all variables, but is only significantly so for hours worked, whereas the international backward linkages are also statistically significant for nominal value added growth.

[24] Running a regression between the growth of capital and growth of the stock of robots while including fixed FEs (as those in Equation (7)) shows that these two variables are not significantly correlated with each other. This might suggest that new robots could be replacements for outdated machineries.

Table 7: Estimated relationship between the growth of robots and industry-level outcomes

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$\Delta \ln EMP_{cit}$	$\Delta \ln HEMP_{cit}$	$\Delta \ln LSH_{cit}$	$\Delta \ln VA_{cit}^{real}$	$\Delta \ln VA_{cit}^{nominal}$
$\sum_{k=0}^{3} \beta_1^k \Delta \ln R_{ci,t-k}$	.006**	.003	0	.022***	.005
F-test of joint significance	(.045)	(.246)	(.96)	(0)	(.205)
$\sum_{k=0}^{3} \beta_2^k \Delta \ln R_{ci,t-k}^{dom-BW}$	.012	.031	.021	-.017	.022
F-test of joint significance	(.536)	(.248)	(.209)	(.543)	(.433)
$\sum_{k=0}^{3} \beta_3^k \Delta \ln R_{ci,t-k}^{int-BW}$	.041	.071	-.051	.01	.175***
F-test of joint significance	(.346)	(.121)	(.249)	(.881)	(.003)
$\sum_{k=0}^{3} \beta_4^k \Delta \ln R_{ci,t-k}^{dom-FW}$	-.038**	-.044**	.02	-.05*	-.063**
F-test of joint significance	(.014)	(.026)	(.198)	(.067)	(.012)
$\sum_{k=0}^{3} \beta_5^k \Delta \ln R_{ci,t-k}^{int-FW}$	.007	.011	.122***	.024	-.101**
F-test of joint significance	-0.822	-0.701	(0)	(.501)	(.013)
R-sq.	.098	.105	.059	.129	.135
Obs	21410	20965	21399	20832	21399

Note: The sample includes all WIOD countries. Robust standard errors are clustered by country-industry pairs in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. We report P values for the F-test $\beta^0+\beta^1+\beta^2+\beta^3=0$. The size of the coefficients is obtained by summing up the estimated coefficients of the contemporaneous values and the three lagged values. All specifications include country-time fixed effects and industry fixed effects. Regressions are unweighted. Estimated with STATA using the *reghdfe* estimation command.

The effect of the stock of robots along the domestic forward linkages is significantly negative on the outcome variables, except for labour share and real value added growth. This suggests that an increasing stock of robots in an industry downstream to a specific industry under consideration would negatively impact employment in the given industry. For instance, a manufacturing industry downstream to another industry might improve its performance through the installation of robots as observed in the positive coefficient of the direct effects. However, the industrial capacity after the installation of new robots will negatively impact the industries upstream, i.e. through their forward linkages to this downstream industry. One reason might be that the new machinery in the downstream industry requires less demand for inputs from the upstream industries. Another reason could be that digitalization in a downstream industry allows industries to take over some tasks previously undertaken in the upstream industries. Therefore, when new robots are installed in a downstream industry, the upstream industries are negatively affected.[25]

As a further robustness check, the estimation results including only the growth of robots (i.e. excluding TFP variables) are presented in Table 7 and indicate that the results are qualitatively similar.

5.2. Quantitative implications based on model predictions

5.2.1. Total economy impacts

In the next step, the estimation results presented in Table 6 are used to retrieve the implied contribution of robots growth on changes of employment and real value added. The focus is first on employment because the digital transformation debate is very much geared towards the consequences for labour demand. Moreover, aggregate real value added as a measurement on growth of global GDP is another important factor that could be stimulated by robots, in particular, and by Industry 4.0, in general.[26].

The annual effect of the growth of robots on employment growth ($\Delta lnEMP$) and on real value added ($\Delta\, ln\, VA_{cit}^{real}$) is calculated by applying the estimated coefficients of the direct and indirect effect through input-output linkages to the employment-weighted average of the log growth in the stock of robots (ΔlnR). The predicted effects at the aggregate country group level on any of the outcome variables EMP or VA^{real} is retrieved in the following way:

$$\widehat{\Delta lnY_t^{\mathrm{E}}} = \sum_{k=0}^{3} \hat{\beta}_1^{kY} \sum_{c}^{C}\sum_{i}^{I}\left[\left(\frac{1}{T}\cdot\sum_{t}^{T}\frac{Y_{cit}}{Y_t}\right)\Delta lnR_{cit}^{\mathrm{E}}\right], \tag{9}$$

$$Y \in \{\mathrm{EMP}, \mathrm{VA^{real}}\}, \qquad \mathrm{E} \in \{\mathrm{Direct}, \mathrm{dom-BW}, \mathrm{int-BW}, \mathrm{dom-FW}, \mathrm{int-FW}\}$$

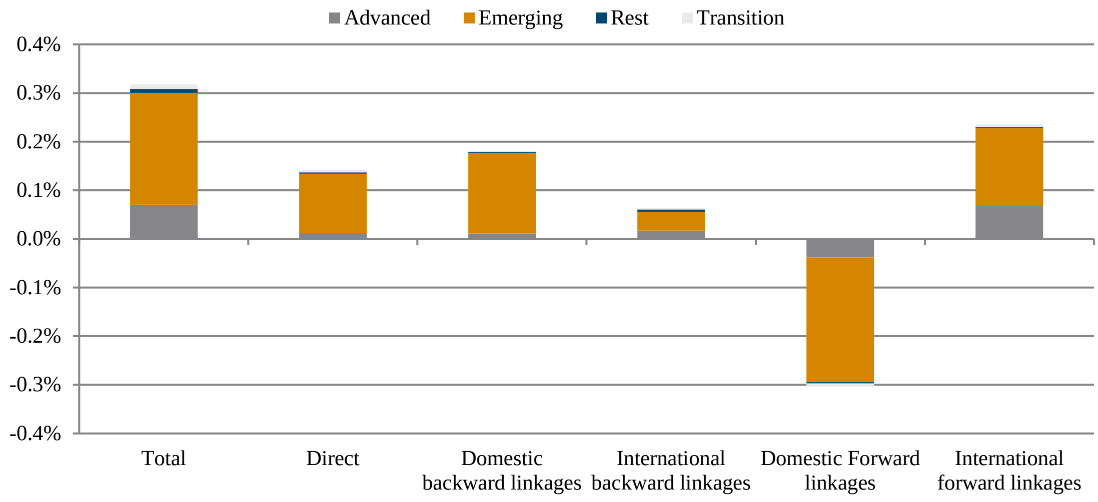
where $\widehat{\Delta lnY_{\Phi}^{\mathrm{E}}}x_t$ is the predicted average annual growth of the outcome variable (i.e. either employment EMP or VA^{real}). $\sum_{k=0}^{3}\hat{\beta}_1^{kY}$ is the estimator reported in Table 6 of Variable E of the growth of the stock of robots that denoting the direct effects ΔlnR_{cit}, domestic backward linkages $\Delta lnR_{cit}^{\mathrm{dom-BW}}$, international backward linkages $\Delta lnR_{cit}^{\mathrm{int\_BW}}$, domestic forward linkages $\Delta lnR_{cit}^{\mathrm{dom-FW}}$ and international forward linkages $\Delta lnR_{cit}^{\mathrm{int-FW}}$ on a given outcome variable Y. T

[25] These impacts have to be studied in more detail, however.

[26] Certainly, there is also great interest in distributional issues, of which one dimension—the function distribution—could be captured by the labour share. However, since the model specification for labour share performs very poorly, model predictions for the labour share are omitted.

denotes the total number of years of the sample and therefore $\left(\frac{1}{T} \cdot \sum_t^T \frac{Y_{cit}}{Y_t}\right)$ is the period-averaged share of the outcome variable. Applying this methodology yields global outcome effects for the global group sample on average, which are summarized in Figure 6.

Figure 6: Predicted effects of the growth of robots on economy-wide employment, WIOD average



Note: Coefficients are applied to the weighted averages of the growth rates of the stock of robots across countries and industries. Coefficients are taken from estimations in Table 6 (for employment).
Source: Own calculations.

The overall calculated effects are rather small. For example, the average direct effect of the growth in the stock of robots across all countries and industries implies employment growth by about 0.14 per cent per annum. Interestingly, the positive direct effect is reinforced by the domestic (0.18 per cent) and international (0.06 per cent) backward linkages. These, however, are compensated for by the—in relative terms—quite strong negative domestic forward linkages (-0.3 per cent) whereas the international forward linkages have a positive impact (0.24 per cent). The overall result is therefore a positive employment effect of 0.3 per cent per annum (compared to the 1.7 per cent growth rate of employment in the world economy). One should note, however, that according to Table 6, significant effects are only found for the direct effect and the domestic forward linkages. If only these effects are taken into account, the effect is negative at -0.16 per cent. The overall joint effect related to robots growth, however, is statistically significant at the 10 per cent level (not at the 5 per cent level)[27]. This might indicate that it is still too early to detect sizeable employment effects as a result of the introduction of new robots, which is in line with

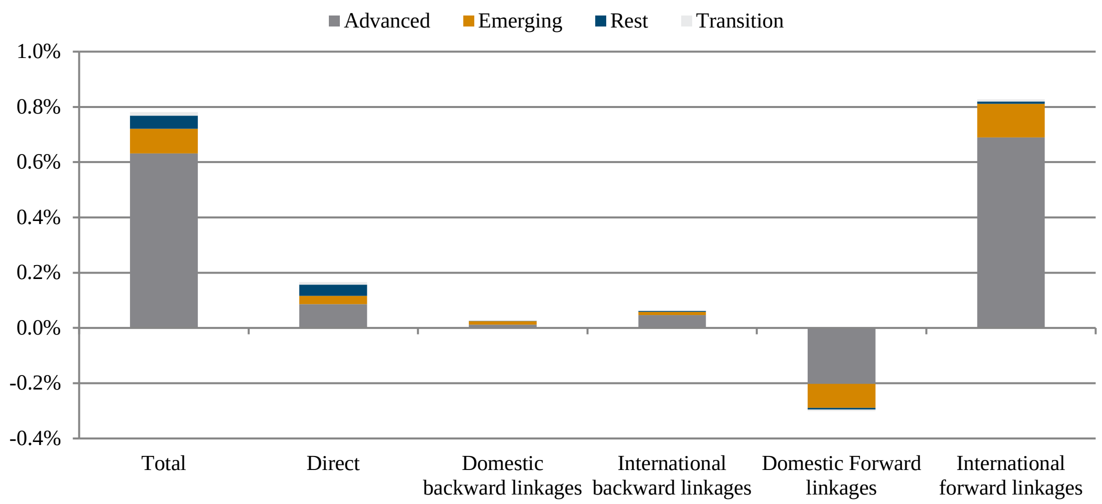
[27] This joint significance is the F-test with the null hypothesis that the summation of all coefficients in the estimation is equal to 0, and is not rejected at the 10 per cent level of significance.

Graetz and Michaels (2018) who also report no measurable effect of robots growth on overall hours worked.[28]

These overall effects can be divided along the groups of countries defined above. The bulk of the effects stem from the emerging economies characterized by high growth rates of robots (as shown in Table 1) and high employment growth rates (Table 2). Furthermore, these countries' employment shares are relatively high due to lower productivity levels. The developments in the transition economies and the remaining countries do not contribute to the explanations of global patterns.

Figure 7 shows the predicted average effects of growth in the stock of robots on global real value-added growth and indicates that about 0.8 per cent of growth is explained by the increase in the number of robots, with direct effect accounting for 0.17 per cent. The main positive impact comes from international forward linkages. As one can see, when considering value added growth, advanced economies (due to their higher share of value added in the world economy) provide the largest contribution to the main effect.

Figure 7: Predicted effects of the growth of robots on economy-wide real value added, WIOD average



Note: Coefficients are applied to the weighted average value added in the change in the stock of robots across countries and industries. Coefficients retrieved from estimations in Table 6.
Source: Own calculations.

[28] It should be noted, however, that total employment effects related to robots on the increase in hours worked in this study is statistically significant at the 10 per cent level and equal to 0.07 per cent.

5.2.2. Employment growth effects in the origin perspective

Another interesting aspect regarding the robots-induced employment effects is the distribution of effects across countries and industries. As pointed out by AS (2018), we can view employment creation (or destruction) from two different perspectives. The first perspective is the *destination* perspective which corresponds directly to the estimated model and is calculated like in Equation (9). In this case, employment changes are assigned to the industry where additional employment is generated or reduced.

The second perspective is the *origin* perspective. In this approach, we examine which country or industry has introduced new robots and is therefore originally responsible for the employment (or value added) generated in the destination country or industry. To switch from the destination to the origin perspective, the elements in Equation (9) need to be rearranged. By inserting Equations (3) and (4) in Equation (9) and rearranging the shares with Leontief or Ghosh coefficients, we can derive the following equation to predict the employment (or value added) contribution that originated from each industry as a supplier or as a customer. Compared to Equation (9), this basically results in a specification that sums the linkages over the rows rather than the columns:

$$\Delta lnY_t^{\widehat{\mathrm{E_{dom}}-\mathrm{origin}}} = \sum_{k=0}^{3} \hat{\beta}_1^{kY} \sum_{c}^{C} \sum_{j \neq i}^{J} \Delta lnR_{cjt} \left[\sum_{i}^{I} \left(\frac{1}{T} \cdot \sum_{t}^{T} \frac{Y_{cit}}{Y_t} \right) \Gamma_{cjt,cit} \right], \tag{10}$$

$$Y \in \{EMP, VA^{real}\}, \mathrm{E} \in \{dom - BW\ , dom - FW\}, \qquad \Gamma \in \{l, g\}$$

$$\Delta lnY_t^{\widehat{\mathrm{E_{int}}-\mathrm{origin}}} = \sum_{k=0}^{3} \hat{\beta}_1^{kY} \sum_{c}^{C} \sum_{j \neq i}^{J} \Delta lnR_{cjt} \left[\sum_{i}^{I} \left(\frac{1}{T} \cdot \sum_{t}^{T} \frac{Y_{cit}}{Y_t} \right) \sum_{f \neq c}^{F} \Gamma_{fjt,cit} \right], \tag{11}$$

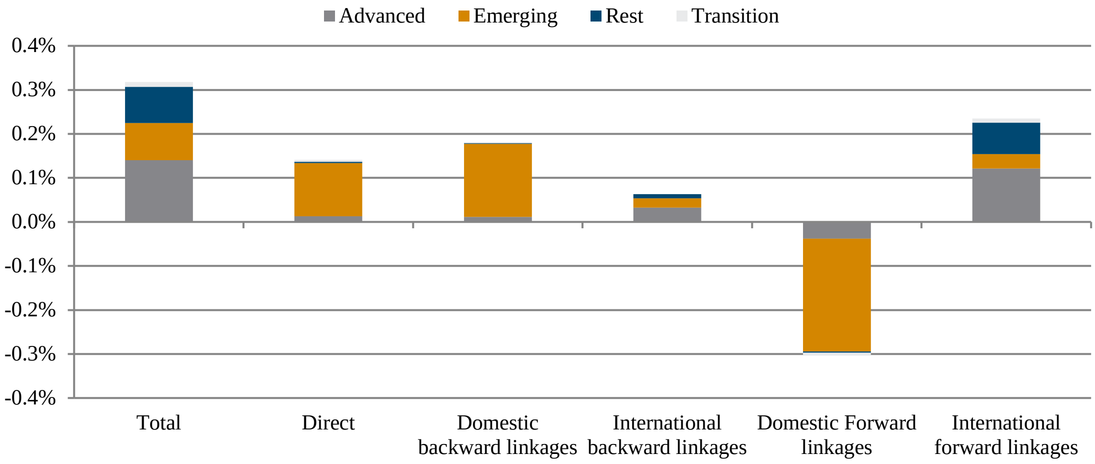
$$Y \in \{EMP, VA^{real}\}, \quad \mathrm{E} \in \{int - BW\ , int - FW\}, \qquad \Gamma \in \{l, g\}$$

In Equation (10), $\Gamma_{cjt,cit}$ is either the domestic Leontief inverse $l_{cjt,cit}$ for the calculation of domestic backward linkages ($\mathrm{E} = dom - BW$) or the Ghosh inverse $g_{cjt,cit}$ for the calculation of domestic forward linkages ($\mathrm{E} = dom - FW$); in Equation (11), $\Gamma_{cjt,cit}$ is either the Leontief inverse $l_{cjt,cit}$ for the calculation of international backward linkages ($\mathrm{E} = int - BW$) or the Ghosh inverse $g_{cjt,cit}$ for the calculation of international forward linkages ($\mathrm{E} = int - FW$) used. Figure 8 presents the results of this exercise.

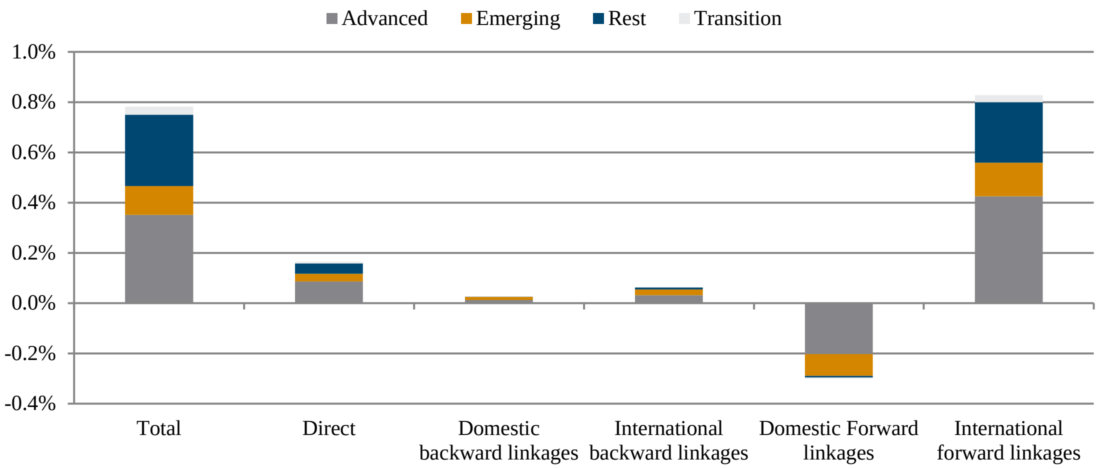
With respect to employment, the patterns of the direct and backward and domestic forward linkages are similar to those in the destination perspective. Interestingly, however, the contribution of the rest of the countries (including the Central and Eastern European countries and Taiwan Province of China) is much more prominent via international forward linkages, which also results in a stronger overall effect for these countries. A similar pattern is found when considering value added growth.

Figure 8: Predicted effects of the growth of robots in the origin perspective, WIOD average

Employment growth



Real value added growth



Note: Coefficients are applied to the weighted average value added in the change in the stock of robots across countries and industries. Coefficients retrieved from estimations in Table 6.
Source: Own calculations.

A similar perspective can be taken when distinguishing the effects by industry group. Table 8 reports the employment and real value added effects by four groups of industries (similar to the above figures).

Table 8: Effects by industry

Origin perspective

	Total	Direct	Domestic backward linkages	International backward linkages	Domestic forward linkages	International forward linkages
Employment						
Primary	0.08%	0.06%	0.01%	0.01%	-0.02%	0.02%
Manufacturing	0.21%	0.05%	0.15%	0.05%	-0.26%	0.21%
Robotized services	0.04%	0.03%	0.02%	0.00%	-0.03%	0.01%
Non-robotized services						
Total	0.32%	0.14%	0.18%	0.06%	-0.30%	0.24%
Real value added						
Primary	0.02%	0.01%	0.00%	0.00%	-0.02%	0.03%
Manufacturing	0.74%	0.14%	0.02%	0.06%	-0.25%	0.77%
Robotized services	0.02%	0.02%	0.00%	0.00%	-0.03%	0.02%
Non-robotized services						
Total	0.78%	0.17%	0.03%	0.06%	-0.30%	0.83%

Destination perspective

	Total	Direct	Domestic backward linkages	International backward linkages	Domestic forward linkages	International forward linkages
Employment						
Primary	0.08%	0.06%	0.04%	0.01%	-0.08%	0.05%
Manufacturing	0.13%	0.05%	0.04%	0.02%	-0.05%	0.06%
Robotized services	0.04%	0.03%	0.03%	0.01%	-0.11%	0.06%
Non-robotized services	0.07%	0.00%	0.06%	0.02%	-0.07%	0.06%
Total	0.32%	0.14%	0.18%	0.06%	-0.30%	0.24%
Real value added						
Primary	0.02%	0.01%	0.00%	0.00%	-0.02%	0.02%
Manufacturing	0.36%	0.14%	0.01%	0.03%	-0.06%	0.25%
Robotized services	0.12%	0.02%	0.00%	0.01%	-0.07%	0.16%
Non-robotized services	0.28%	0.00%	0.01%	0.02%	-0.16%	0.40%
Total	0.78%	0.17%	0.03%	0.06%	-0.30%	0.83%

Note: Coefficients are applied to the weighted average value added in the change in the stock of robots across countries and industries. Coefficients retrieved from estimations in Table 6.
Source: Own calculations.

Looking first at the direct effect (which is the same in the destination and origin perspectives), we find that the direct effect is relatively stronger in manufacturing for real value added growth (0.14 per cent) whereas it is more equally distributed with respect to employment growth (though again being larger for primary industries and manufacturing). Not surprisingly, we find that the impact via backward and forward linkages is also much stronger for manufacturing in the origin perspective because robot adoption mostly originates in manufacturing. By definition, the direct impact of services industries not using robots is 0. This also explains that the total effect on employment and real value added growth is mostly driven by robots in manufacturing in the origin perspective. In the destination perspective, these patterns are much more similar across groups of industries indicating spillover effects from the use of robots in manufacturing in the other industries (including services not using robots).

6. Summary

This study has analysed the role of robotization in the global economy by exploring the spillover effects of the impacts of TFP growth and robotization on the global value chains (GVCs). By applying and extending the distributed lag econometric framework applied by Autor and Salomons (2018) (AS), we analysed the impact of the growth in the stock of installed multipurpose industrial robots on employment and value-added industrial growth across 41 countries. Using the World Input-Output Database (WIOD), we extended their framework to include backward and forward international linkages in addition to the respective domestic linkages AS used in their econometric analysis. Further, while AS used industrial total factor productivity (TFP) growth as the main indicator of technological advancements, we included industrial robots as well, which is interpreted as a measure of recent technological advancements. The initial findings of our analysis indicate that the results obtained by AS were sensitive to the specifications and the sample selection of the econometrics. After adding more countries to the sample of AS, the direct impact of industrial TFP growth on employment growth became positive and statistically insignificant.

In a more sophisticated econometric specification using industry fixed effects instead of aggregate sector fixed effects controlling for industrial long-term technological heterogeneity, the results shed light on various aspects of the effects of industrial robots on different industrial outcomes. Growth in the stock of industrial robots in an industry improves both the growth in employment growth and real value added of the respective industry at a 1 per cent level of significance. Growth in the stock of industrial robots among suppliers of an industry that is accumulated along the domestic supply chains and that accumulated along the international backward linkages improve the number of hours worked, while the latter also improves real value added. However, growth in the stock of robots in domestic forward linkages reduces employment and value added growth. Moreover, growth in the stock of robots in international forward linkages reduces real value added growth.

We finally show the contribution of the stock of robots on employment and value added across various industries and countries distinguishing the effects from an origin perspective and a destination perspective. The origin perspective is the industry in which the new robots were installed and the destination is the industry whose outcome variable of interest (i.e. employment or value-added growth) was influenced by the growth in the stock of robots in the origin industry via value chains. Here, interesting patterns of the interaction, and therefore the differentiated impacts, between manufacturing and services are documented.

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Appendix

Appendix Table A 1: WIOD countries in the sample of study

Country code (ISO 3 digit)	Country	Group
AUS	Australia	Advanced
AUT	Austria	Advanced
BEL	Belgium	Advanced
CAN	Canada	Advanced
DEU	Germany	Advanced
DNK	Denmark	Advanced
ESP	Spain	Advanced
FIN	Finland	Advanced
FRA	France	Advanced
GBR	United Kingdom	Advanced
GRC	Greece	Advanced
IRL	Ireland	Advanced
ITA	Italy	Advanced
JPN	Japan	Advanced
KOR	Rep. of Korea	Advanced
LUX	Luxemburg	Advanced
NLD	Netherlands	Advanced
NOR	Norway	Advanced
PRT	Portugal	Advanced
SWE	Sweden	Advanced
USA	United States	Advanced
BRA	Brazil	Emerging
CHN	China	Emerging
IDN	Indonesia	Emerging
IND	India	Emerging
MEX	Mexico	Emerging
TUR	Turkey	Emerging
BGR	Bulgaria	Transition
ROU	Romania	Transition
RUS	Russian Federation	Transition
CHE	Switzerland	Rest
CYP	Cyprus	Rest
CZE	Czech Republic	Rest
EST	Estonia	Rest
HRV	Croatia	Rest
HUN	Hungary	Rest
LTU	Lithuania	Rest
LVA	Latvia	Rest
MLT	Malta	Rest
POL	Poland	Rest
SVK	Slovakia	Rest
SVN	Slovenia	Rest
TWN	Taiwan Province of China	Rest

Source: WIOD, own assessment.

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