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Are Industrial Robots a new GPT? A Panel Study of Nine European Countries with Capital and Quality-adjusted Industrial Robots as Drivers of Labour Productivity Growth

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Summary:

In recent years, the interest in the field of economic research in studying the effect of robots on economic outcomes, i.e., labour productivity, labour demand and wages, has increased from an individual country perspective as well as for country groups. By using a fixed effects panel modeling approach, this study of nine robot intensive European countries shows that the core characteristics of a general purpose technology (GPT) are already satisfied by industrial robots. In 2019, seven countries in the panel, i.e. Germany, Italy, France, Spain and the UK (top 5), Sweden (7th) and Austria (10th) - in terms of operational stocks - were among the top 10 of robot using European countries (excl. Turkey). Following the understanding of a GPT of Bresnahan/Trajtenberg (1995), six panel regression models were estimated and linked to the four main characteristics of a GPT. Accordingly, two new measures are proposed in this paper; the first one is named the Division of Labour (or DoL) and is constructed by building the ratio of labour productivity inside the manufacturing industry to labour productivity across all industries. The second one is the Robot Task Intensity Index (RTII), which accounts for the number of tasks that a robot was used for in different production processes across the nine European countries. A high level of fulfilled tasks implies a higher quality of robot as the number of potential tasks, which the robot can perform, is an important criterion for the quality of that robot. In accordance with the GPT literature, both measures showed the expected (in) significances. At the bottom line, all six models underlined the economic relevance of industrial robots for the nine European countries included in the analysis and give a strong indication that robots can indeed be seen as a new general purpose technology.

Zusammenfassung:

Im Rahmen der ökonomischen Forschung nehmen Industrieroboter eine an Bedeutung zunehmende Rolle ein. Zu den häufigsten Untersuchungsfeldern zählen die Fragen, wie Roboter auf die Produktivität, die Beschäftigung und die Löhne wirken. Methodisch ist hierbei zwischen Studien zu unterscheiden, die diese Effekte für ein einzelnes Land untersuchen und solchen, die mehrere Länder (-gruppen) betrachten. Für Ländergruppen werden oftmals Panelanalysen verwendet. Die vorliegende Arbeit zeigt für neun roboterintensive europäische Länder im Rahmen eines Fixed Effects Ansatzes, dass Roboter bereits wesentliche Charakteristika einer Basistechnologie erfüllen. Von den Ländern mit den höchsten absoluten Roboterbeständen in Europa (unter Nichtberücksichtigung der Türkei) sind mit Deutschland (1.), Italien (2.), Frankreich (3.), Spanien (4.), UK (5.), Schweden (7.) und Österreich (10.) die Top-5 vollständig und die Top-10 mehrheitlich im Panel vertreten. In Anlehnung an die Beschreibungen der Charakteristika einer GPT von Bresnahan/Trajtenberg (1995), wurden sechs Regressionsmodelle geschätzt und den vier Eigenschaften einer Basistechnologie zugeordnet. Zudem wurden zwei neue Maße entwickelt, der *DoL* und der *RTII*. Der DoL beschreibt den Grad der Arbeitsteilung in einer Volkswirtschaft und berechnet sich als Quotient aus den Arbeitsproduktivitäten im Sektor *Manufacturing* und im Sektor *Total Industries*. Der RTII beschreibt den Anteil an Aufgaben, die ein Roboter zu einem Zeitpunkt t erfüllt, gemessen an der Gesamtheit aller möglicher Aufgaben, die für Industrieroboter gem. der IFR Klassifizierung prinzipiell ausführbar sind. Es bildet somit ein Maß für die Qualität der Roboter. Sowohl die zwei neu eingeführten Maße, als auch die übrigen Variablen in den 6 Modellen weisen die in der Literatur beschriebenen erwartbaren Vorzeichen und Größenordnungen auf. Die Ergebnisse der Untersuchung deuten darauf hin, dass Roboter eine neue Basistechnologie darstellen.

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1. Introduction

The influence of industrial robots on economic outcomes is a topic, which has increasingly garnered the attention of researchers in academia as well as of economic policymakers. Since 2004, the European Commission has intensified their funding for cognitive systems, robotics and AI. During that time, funding in the range of €80 million per annum was spent on new projects, including up to 20 new collaborative projects every year (under Horizon 2020). Between the years 2014 and 2018, roughly €87 million was invested into robotic projects under Horizon 2020, e.g., in the form of Public Private Partnerships. For research and economic application purposes, the annual European Robotics Forum was launched in 2009. As with other modern technologies, the effects that are attributed to robots are considered as being drivers of rising output and productivity. For many industrialized countries, the annual growth rates of labour productivity (LP) are moderate but still positive. Hence, certain questions arise about the size of the effect that robots - as a specific example of a process innovation - have on labour productivity, whether the effects are appropriately measured (taking into account the Solow Paradox) and if they lead to future LP growth. Basically, the question arises as to if these aspects imply that robots can be classified under the term general purpose technology (GPT). Therefore, the aim of this paper is to show how robots affect labour productivity in nine European countries in comparison to other capital goods over the time between 1995 and 2015. The premise is that robots are an innovative factor of production and as such - in line with several other studies - increase labour productivity but do so less strongly than aggregated capital goods. Moreover, it is suggested that the productivity effects of robots and some of the other capital goods tend to go in the same direction while other capital goods have either no or indeed opposite effects on labour productivity. The sign depends on whether other capital goods are gross complements or substitutes in the macroeconomic production of value added.

The outline of the paper is as follows: In Section 2, the understanding of a GPT is used to discuss whether and under which circumstances robots can be considered as a GPT (2.1). Section 2.2 reflects current empirical studies that consider the effect of robots on labour productivity, while Section 3 describes the underlying data and stylized facts. In Section 4, several aspects of being a GPT are tested empirically inside a multi-model panel framework. Each model links to a specific hypothesis (posited in 4.1) addressing different characteristics of a GPT. Firstly, the general premise that robots contribute (significantly) to labour productivity is verified with different capital goods (model M1); next, by introducing an innovative, self-defined measure - the task intensity of robots (RTII) - the quality improvement of industrial robots and the subsequent effects on labour productivity are estimated (M2). In a third model (M3), the ratio of gross output and value added was used to check whether robots attend to increase the degree of division of labour. For a further model specification (M4), a quadratic term - as in Scherer (1989) - is used to capture potential returns to scale. The fifth model (M5) captures the effects of robots over sub-periods of time using a split data set to analyze the time dimension that is needed for robots to generate their full productive gains throughout the economy. Finally, the hypothesis of whether robots lead to capital augmentation is analyzed in model 6 (M6). In Section 5, the results from the aforementioned empirical models are discussed with the aim of answering the question of whether industrial robots in the EU can be considered as a GPT (yet). To answer this question, data on industrial robots in nine European countries - 8 of which belong to the top 9 European countries with the highest robot intensities with the exception of Belgium which is not taken into account because capital data are not reported in the EU KLEMS database - plus the UK are considered.

2. Theory and Methodological Approach

2.1. Industrial Robots: Arguments for the Existence of a New General Purpose Technology

Are robots (becoming) a new general purpose technology? To address the question of whether the term GPT is appropriate to describe the effects of robots it is firstly necessary to define what characteristics are typically associated with a GPT in the literature. The understanding of GPTs is linked to what Landes (2008) refers to as an industrial revolution, i.e., the substitution of labour with machinery and, in more detail, industrial revolutions, i.e., different waves of technological change, e.g., textile manufacturing, the iron industry, the steam engine, machine tools, chemicals, and transportation. The term GPT was introduced by Bresnahan and Trajtenberg (1995), who developed a more conceptual understanding of what constitutes a GPT. The authors characterize a GPT by four dimensions:

i. Pervasiveness (they are used as inputs by many downstream sectors),

ii. an inherent potential for technical improvement,

iii. innovational spawning and

iv. returns to scale.

For the purpose of this work, innovational complementarities are summarized under the term 'innovational spawning' as in Jovanovic and Rousseau (2005). A technology that fulfills all of the aforementioned criteria is called a GPT. Pervasiveness cannot directly be accounted for in a macro study and is therefore expressed indirectly via the effects of robots on labour productivity and the effects at the national level on the degrees of division of labour (Figure 1). Two main characteristics of innovational spawning - decreasing prices and/or an increasing level of quality - mentioned by Jovanovic and Rousseau, can already be detected on the macro level as the real and quality-adjusted prices of robots are decreasing in the main industrialized countries (Dauth et al., 2017). Due to missing information concerning the quality and prices of robots in the International Federation of Robotics (IFR) dataset, these aspects cannot be dealt with in this study.

Criterion iv. leads to the conclusion that a GPT is essentially a drastic innovation with the inherent potential of deterring market entry (see, e.g., Salop (1979), Ellison and Ellison (2007), Wilson (1992) and Tirole (2011)). The positive achievement of GPTs can be seen in sharp contrast to the potential of becoming 'drastic innovations'. Usually it takes some time for the innovating firm behind a GPT to earn a profit from its innovation. Rising implementation costs could hamper the adoption of the technology (e.g., as it is secured by patents), which lowers the social benefit of the innovation. The inventors of drastic innovations could generate long-term benefits from early market entries by achieving monopoly profit shares and deterring the subsequent market entry of potential competitors. Hence, the diffusion process of an innovation and thus the level of innovation is artificially reduced, where knowledge serves as a factor of competitive advantage.

Both views on GPTs, as radical innovations with and without the tendency to become drastic innovations, receive support from literature: The former line of argumentation can be found in Olmstead-Rumsey (2019). The author sees a decline in radical innovations (more precisely, firms who own radical innovations) as a reason for market concentration and the productivity slowdown in the US. On the other hand, the perspective of GPTs eliminating market concentration is supported by Aghion et al. (2014). Both perspectives might be combined in such a way that in the early stages of newly introduced goods, there will be a tendency for labour-saving technology as well as for monopolistic rents. In the long run, a capital-augmenting process may follow if the innovation level cannot be matched by other market competitors, such that there is a potential for monopolistic rents (price > average costs).

This would lead to the observation of new technologies being primarily capital-augmenting. If this profitable position is not time-persistent, i.e., new innovators emerge as rivals for the enlarged market shares of the former pioneer, this can lead to the innovation becoming a GPT and reducing the additional market shares of the former monopoly. This development is in line with the empirical development of many industrialized countries (see Karabarbounis and Neiman (2014)). One reason why labour productivity (and the labour income share) in the long run remains (almost) constant is mentioned by Acemoglu (2003) by referring to the time dimension such that in the short term, imbalanced growth paths are observed but tend to diminish over the longer term. If it was otherwise, the capital-deepening technology would transform into a persistent example of capital-augmenting technical progress, this would than contradict the idea that the innovation is a GPT. A productivity slowdown would then necessarily follow a time-persistent increase of capital intensity. Brynjolfsson et al. (2017) determine four aspects as to why a GPT might be associated with a disproportional increase or even a stagnation of productivity growth:

1) False hopes,
2) mismeasurement,
3) concentrated distribution and rent dissipation and
4) implementation and restructuring lags.

As throughout this study, two of the most frequent used economic output measures are used directly in the case of valued-added, and indirectly in the case of gross output, the first and second argument are left for political debates. The third argument on the contrary seems highly interesting with regard to an empirical investigation as it implies that the benefits of the new technologies are being enjoyed by only a relatively small fraction of economic decision-makers. If that is the case, productivity gains are too small as Brynjolfsson et al. (2017) state, i.e., that particularly technologies that are ‘narrowly scoped’ and rivalrous in nature create wasteful gold rush-type activities. That is because the allocation of resources is placed into reducing competition by deterring the entry of rival firms or into seeking to be one of the few beneficiaries, which destroys many of the benefits of the new technologies. Andrews et al.

(2015) have shown that there is a gap between the innovation frontier and average firms, which has been increasing over the last years. Either this contradicts the idea of GPT's harmonizing with economic competition and welfare, or it undermines the practical relevance of GPTs. The fourth explanation allows both contrary aspects of the Solow Paradox to be correct, such that the Solow Paradox is only a temporary phenomenon. The core of this story is that it is more expensive (in terms of additional required investment and due to opportunity costs, i.e., the time it takes until new innovations are accepted inside each working-field of a firm) than it is generally assumed to implement and exploit new technologies. This is essentially true for those new technologies that qualify as GPTs. Indeed, the more profound and far-reaching the potential of an innovation is, the more likely is the necessity of a restructuring process inside (heterogeneous) firms and thus the longer the time lag will become between the initial invention of the technology and its full impact on the economy.

Another stream of literature discusses the distinct relation between GPTs and productivity more critically. Lipsey et al. (2005), for instance, use the concept of a transforming GPT, i.e. a technology that transforms many parts of an economy. The effects on productivity are not seen as deterministic as they reject not only the idea that each GPT necessarily has to contribute to productivity gains but also that there is a cumulative gain function of past GPTs. In the end, Lipsey et al. (2005) deny the ability of a production function to accurately capture productivity developments. Furthermore, they state that the time (or what is referred to as the time lag in Brynjolfsson et al. (2017)) needed to disclose the productivity gains, might differ among GPTs. As a consequence, there would be no longer be a contradiction between slow productivity contributions and a significant overall (i.e., cumulative) effect as this would mean a more continuous spread with a higher probability of long-term necessity, in comparison to a "one hit wonder" technology. The main difference appears for aspect iv. which is further subdivided by Lipsey et al. (2005) into Static and Dynamic Externalities (S.E. vs. D.E.). Whereas S.E. capture spillover effects without changing the Walrasian character of the economy, D.E. refer to any sort of scale economies (at the intra-industry and/or intra-firm level). While D.E. seem most interesting in characterizing innovations as GPTs, this aspect - due to data limitations - cannot be further elaborated on in this paper. Therefore, only an extant understanding of returns to scale is used.

Summarizing the different considerations about GPTs, one can state that industrial robots not only directly increase labour productivity they also help other GPTs to spread throughout the economy. Hence, robots seem to be a natural example for a GPT in the sense of Bresnahan and Trajtenberg (1995) and those of Carlaw and Lipsey (2002) and Lipsey et al. (2005).

2.2. Related Studies

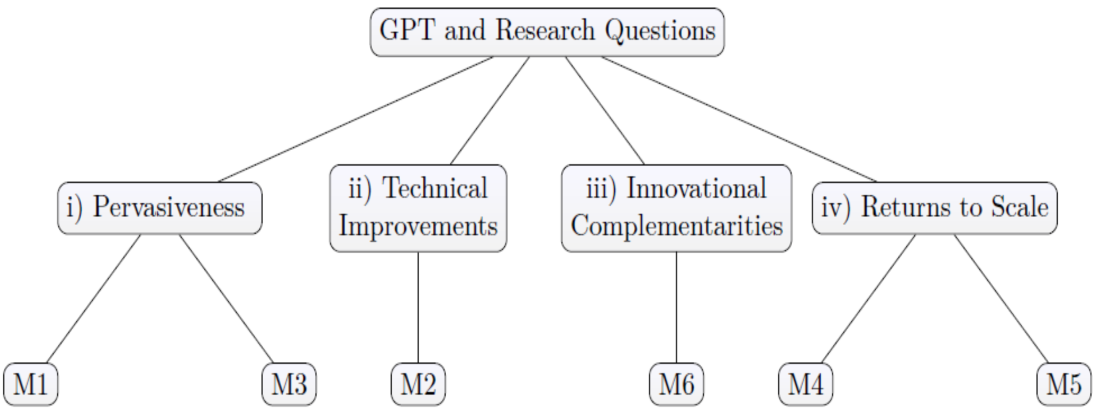
Several studies shed light on the connection between robots and economic growth. Central to most of the research papers in this area is the concept of a neoclassical production function, mainly a Cobb-Douglas or CES-type function is discussed, whereby robots are captured as an additional input. A theoretical contribution is offered by DeCanio (2016) who shows for different production specifications the potential effects of robots on the functional income distribution. Graetz and Michaels (2015), Kromann et al. (2016) and Jungmittag and Pesole

(2019) use the Cobb-Douglas production function as a starting point for their respective empirical analyses. This concept is then used to estimate the functional relationship between the innovative input measure and the economic outcome, i.e., the contribution that robots play in terms of economic growth. All of these studies employ a panel data approach. In a more recent research contribution, Jungmittag uses a convergence testing approach to analyze whether robot densities inside EU manufacturing sectors are drivers of labour productivity convergence or divergence. Using data from the EU KLEMS database, the author finds for 24 EU countries between 1995 and 2015 that robots per €1 million of non-ICT capital input contribute significantly to labour productivity growth. While there was no empirical evidence for convergence for the first period (1995-2004), there is relatively fast conditional and unconditional convergence for the second period from 2005 to 2015 (Jungmittag, 2020). Dauth et al. (2017) show for Germany that an increase in robots per 1,000 workers increases labour productivity (measured as GDP per person employed) between 2004 and 2014 by 0.5%. Graetz and Michaels (2015) find that industrial robots increased both value-added and labour productivity for 17 countries between 1993 and 2007. The use of robots raised countries' average growth rates by about 0.37 percentage points. Graetz and Michaels (2015) also find that robots had no significant effect on total hours worked. Kromann et al. (2016) find, for 9 countries and 11 industries, that a one standard deviation increase in robot intensity (measured as the number of industrial robots per €1 million non-ICT capital) effects a total factor productivity increase of roughly 6.6% using a log difference panel approach for the years 2004 and 2007.

The explicit modeling of technical progress is not accounted for in these studies, nonetheless Jungmittag and Pesole (2019 as well as Jungmittag (2020) make use of an implicit measure for technical progress of robots that is related to the procedure used by Graetz and Michaels (2015). By linearly depreciating the industrial robots under the assumption of different life-spans (namely 6, 10 and 20 years, that correspond to 16%, 10% and 5% depreciation rates, respectively), which are lower than the 12 years, one-horse shay depreciation method assumed by the IFR (2017), Jungmittag implicitly accounts for technical change. That is because the new frontier technology replaces the old one, i.e., after each 6, 10 or 20 years, more innovative and thus more productive robots are at work. Due to depreciation, the absolute number of robots decreases in t=6, t=10 or t=20, respectively, and this corresponds to higher robot productivity (Y/R). Krenz et al. (2018), by using a new measure of reshoring activity and data from the WIOD database, find a positive association between reshoring and the degree of automation (i.e., robots per 1,000 workers). On average, within manufacturing sectors, an increase in robot intensity by one robot per 1,000 workers is associated with a 3.5% increase of reshoring activity (relative increase of domestic vs. foreign inputs).

Another stream of gains in productivity, in addition to the rise of innovative factors of production, are attributed to a combination of new inputs with traditional inputs. Ghodsi et al. (2020) interpret the rise of new technologies, e.g., machine learning, artificial intelligence and robotics, as those key technologies that will determine the future combination of input factors and their relations as well as the generation and distribution of value-added across sectors. This view can be expanded to differences across countries, as this development affects not only the competition profile of firms in a given industry but also those of a country. A central premise in Ghodsi et al. (2020) is the idea that productivity gains cumulate over different industries, either via direct productivity effects in the final goods or, alternatively, via indirect effects as more efficient intermediates appear due to the use of robots in the production of non-robot using industries. Examples of which include the provision of personal services such as the customer advisory sector, where firms work with more efficient computers that can do better data analysis and thus improve the quality of the services provided. While the authors argue that this gain in efficiency results in higher product demand that "might eventual lead them [i.e., firms - K.S.] to create higher employment", a labour-saving technology might also be used for further process and product innovations, especially if the final good markets are competitively organized and the outcome is not only a function of prices but hedonic prices. Innovations are, from a theoretical point of view, therefore more likely to hold labour demand stable than expecting a significant outcome from the technology itself or from changes in the firms' optimization calculus. This view is supported by the results of Gregory et al. (2016), who find that an increase in demand for goods, due to lower prices, was necessary to enable positive labour demand in 27 European countries (24 are current member of the EU27 and three are non-EU countries, including the UK).

Figure 1: Research Questions and Empirical Models



Source: Own representation

In Section 4, the central premises for classifying a new technology as a GPT are tested empirically. The methodological approach is described in Figure 1. Measuring *technical improvements* - via the implementation of a newly developed indicator RTII - and *returns to scale* - using a methodological approach described by Scherer (1989) – was relatively straightforward. It should be noted that for the empirical models, some deviations from the theoretical GPT definitions were necessary. That is because the definitions refer to a related intra-firm/intra-industry perspective that cannot be reflected in macroeconomic datasets. This holds particularly true for the application of the terms pervasiveness and innovational complementarities as for both it would be necessary to account for industrial spillover effects. Therefore, a modified understanding of both concepts is required. *Pervasiveness* is thus chosen to be achieved if robots on a macro level show a significant effect on labour productivity (M1) and if robots enhance the division of labour inside the economy (M3). Detecting innovational complementarities is more complicated when it comes to being measured on a macro level. Therefore, if robots do not only tend to increase capital but also lead to capital-enhancing technical change, innovational complementarities are said to be at work. That is the case if robots, as an additional capital input, are not only significant but also increase the significance of traditional capital formations (M6).

3. Data Description

3.1. Variables

The input and output variables were taken from the EU KLEMS database released in September 2017 and revised in July 2018. The only exception was made for the industrial robot variable, which was taken from the IFR Industrial Robots Database 2017. Value-added was currency-adjusted and divided by the national price level in order to derive real valued-added. In a first step for the three countries in the dataset that are not part of the Eurozone, namely the UK, Sweden and Denmark, all values that were reported in national currencies were converted to Euro using historical exchange rates from the finazen.net website.[1] In a further step, the structure of the missing values was analyzed using Little's MCAR test (Little, 1988) and visual inspection. The test results revealed that data were not missing completely at random (Allison, 2009) which would – strictly speaking – rule out estimating the missing values via regression analysis (Hair et al., 2014). Nonetheless, using a simple OLS regression on the cross-sectional level data delivered the most convincing results against other methods that are suggested for dealing with not missing completely at random data, e.g. 'multiple imputation' (Rubin 1987). The reason for this can be easily explained: As data reported in the EU KLEMS database are communicated by the national agencies, a lack of observations in specific variables or at specific points in time naturally include a structural component, which was revealed by Little's MCAR test results. This becomes more obvious when one considers that data were missing for only a few countries with a repetitive element concerning the place of missing data in the dataset (e.g., the first two years were missing for the UK; the last year was missing for Sweden, Italy and again the UK). The missing values appeared solely for the capital variables.

Table 1: Panel Core Variables (1995 to 2015)

Variable	***Description***	***Source***
Industrial Robots	Operational stock, time in use: 12 years	IFR 2017 Database
(Real) Value Added (VA)	Difference between the product price and costs of production	EU KLEMS (9/2017)
HEMPE	Total Hours Worked	See above
Captot	Real fixed capital stock (2010 prices)	See above
CapCTtot	Real fixed capital stock (2010 prices) - Communication Equipment	See above
CapITtot	Real fixed capital stock (2010 prices) - Computing Equipment	See above
CapSoft	Real fixed capital stock (2010 prices) - Computer Software and Databases	See above

Source: Own representation

[1] The reference address is given here: https://www.finanzen.net/devisen/pfundkurs/historisch (last accessed December 7th, 2020).

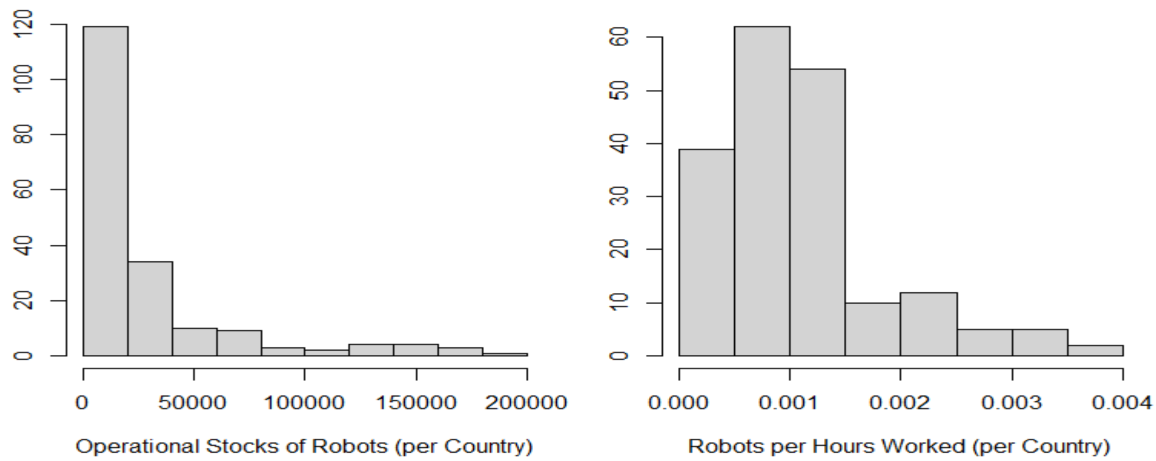
3.2.Distribution of Industrial Robots

The argument for an increase in the level of comparative advantage is in line with being a GPT as robots enhance (further) both process and product innovations. This then leads to an increase of the terms of trade, while competitive advantages arise due to the possibility of incorporating consumer preferences, e.g., by mass-customization, which in the past 30 years raised the demand for a new class of robots that are able to implement mass customization (Eastwood, 1996). According to ISO-8373, the International Federation of Robotics (IFR) defines industrial robots as

'an actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks. Autonomy in this context means the ability to perform intended tasks based on current state and sensing, without human intervention.' (IFR, 2017: 32)

This definition includes *linear robots* (e.g., cartesian and gantry robots), *SCARA robots*, *articulated robots* , *parallel robots* and *cylindrical robots* as well as other type of robots that meet the above mentioned criteria. With the ongoing improvements of robot features in modern manufacturing plants, the definition of industrial robots may at first glance seem somewhat antiquated but the approach makes sure that every robot in use is counted. The following figures show the distribution of robots in the panel (Figure 2). The distribution of robots is far from normal as only a few countries make up for a great majority of the overall stock of robots.

Figure 2: Histograms of Robot Distribution and Robot Densities (per Country)

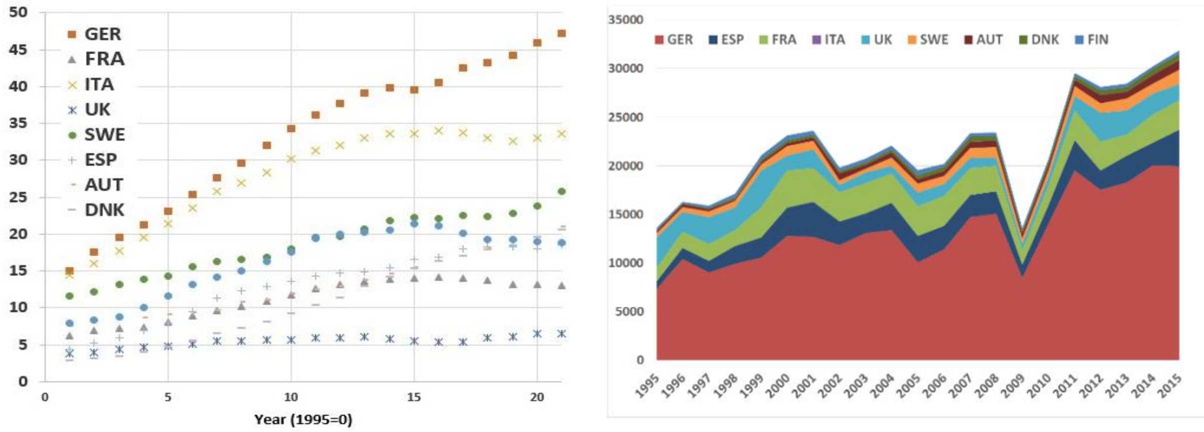


Source: IFR (2017), EU KLEMS (9/2017) - own calculations

Germany is by far the most dominant robot-using country with a rising relative share of between 0.468 (1995) and 0.518 (2015), with a single exception in 2012 (0.258). Despite an absolute increase in terms of the operational stock, the speed of growth was outpaced in this year by other countries, such as Spain, Italy, Sweden and Austria. As a potential reason, one can consider the historical fall in revenue experienced by the German manufacturing sector in the year 2009. This fall had a brief impact in the data such that Germany retook its dominant position for the final five years of the panel. A comparison of the operational stock and robot density (robots by hours worked) shows a higher concentration for the former measure. Thus, robot density shows a lower concentration around the mean so that differences among countries are lower in terms of robot densities than in terms of operational stocks. In addition to the demand for robots, the supply side is briefly presented here in Figure 3.

Therefore, it is not surprising that robot demand and robot supply are both strongly correlated with the size of the manufacturing sector in each country. Hence, there is a strong positive correlation between the rankings of those countries who are at top in terms of producing robots and those who are installing robots. Again, Germany, Spain, France and Italy make up the top 5, as is the case in terms of operational stocks.

Figure 3: Robot Densities and Delivered Robots (per Country)



Source: IFR(2017), EU KLEMS (9/2017) - own calculations

3.3.Capital and ICT Capital Growth

Capital productivity (Y/K) shows how efficiently capital is used to generate output. The growth rate of capital productivity was positive for all three time spans solely for Italy and Sweden. Six out of the nine countries had positive growth rates between 1995 and 2015, whereas Germany, France and Finland suffered from a reduction in capital productivity. Less polarizing was the picture for the first sub-period of the panel (1995-2004), During these 10 years all countries experienced an increase in capital productivity, whereas seven countries went through a decline of capital productivity growth rates during the second sub-period (2005-2015), while at the same time only for Sweden and Italy the capital productivity has increased (Table 2).

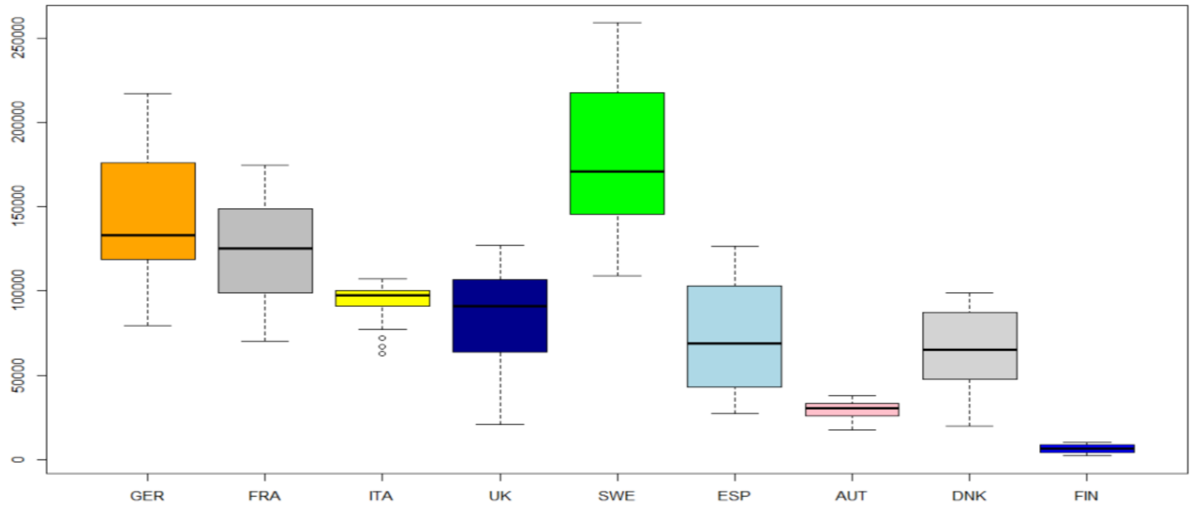
Table 2: Growth Rates of Capital Productivity (Y/Captot)

	1995-2015	1995-2004	2005-2015
Austria	0.006	0.002	-0.109
Denmark	0.006	0.003	-0.089
Spain	0.009	0.0074	-0.016
Finland	-0.0076	0.002	-0.025
France	-0.010	0.0022	-0.0019
Germany	-0.003	0.002	-0.02
Italy	0.009	0.002	0.12
Sweden	0.014	0.013	0.277
UK	0.018	0.0078	-0.036

Source: EU KLEMS (9/2017) – own calculations

While overall capital is a very heterogeneous concept for measuring especially innovative capital input goods, ICT goods are generally accepted as GPT (see, e.g., Basu and Fernald (2007) for the US and Guerrieri et al. (2011) for the EU) and include two aspects that can be considered as relevant for robots to spread their full productivity potential throughout the economy. Thus, ICT capital can be seen as a complementary innovation for robots: Firstly, ICT control elements are necessary in order to use and control robots in order to let them fulfill their intended tasks. Secondly, fast and stable internet connectivity builds the fundamentals of IoT technologies and inter-machine communication, or AI elements such as machine learning, which are becoming more and more integrated into robotic systems. Thus, a positive linkage between robots and ICT equipment and between robots and the quality of internet-connectivity could be seen as sources of labour productivity gains. As data concerning the broadband quality at a national level are scarce, data from cable.co.uk was used for a single year in order to check if there is a high rank correlation between the operational stock of robots and internet quality ($r_{xy} = -0.317$). As this was not the case, using ICT and software capital as regressors appears to be sufficient for the subsequent analysis in this paper.

Figure 4: ICT Capital (per Country)



Source: EU KLEMS (9/2017) - own calculations

Table 3: Growth Rates of ICT Capital Productivity (Y/CapICTtot)

	1995-2015	1995-2004	2005-2015
Austria	0.037	0.007	-0.003
Denmark	0.079	0.006	0.005
Spain	0.076	0.011	-0.065
Finland	0.076	0.007	0.087
France	0.044	0.014	0.328
Germany	0.049	0.079	-0.040
Italy	0.026	0.008	0.071
Sweden	0.042	0.010	-0.099
UK	0.090	0.004	-0.186

Source: EU KLEMS (9/2017) - own calculations

3.4.Labour Productivity Growth

By considering two different time intervals (namely, 1959-1973 and 1973-1995), Jorgensen et al. (2008) find for the US that prior productivity growth is not a good estimator for future labour productivity growth: On average, labour productivity grew roughly twice as fast for the observed data during the first 14 years (2.82) as it did during the subsequent 22 years (1.49). In addition, Brynjolfsson together with his co-authors shows by considering period strings of 10 years that for the US economy, prior labour productivity growth is not a good estimator for future productivity growth (Brynjolfsson et al., 2018). The beta coefficient for both types of productivity were insignificant and the R2 was very low; 0.009 (labour productivity) and 0.023 (TFP).

In contrast to the above mentioned studies, the present work focuses on nine European countries and runs a simple regression; once for the untreated univariate time series and next for the first differenced, non-autocorrelated time series. The results are similar. All of the stationary regressions have insignificant beta coefficients and a low R2, thus implying that growth that occurred 10-years earlier does not contribute to the current growth of labour productivity for the chosen European countries. Out of the nine countries, with the exception of Italy, the UK and Sweden, the majority had a significant intercept, i.e., labour productivity growth was positive on average. These findings again motivate the idea that GPTs are driving labour productivity growth such that unexpected increases and decreases follow one another and that there is no persistent trend; neither positive nor negative. It seems noteworthy that over the whole 20-year period, the annual growth rates of labour productivity and ICT capital productivity were positive for all countries and, in absolute terms, roughly ten times higher than for the individual sub-panels. Additionally, the figure for labour productivity growth contrasted with that of ICT capital productivity growth, which indicates that there are notable differences amongst the countries; concerning the sign and the magnitude. Nevertheless, for all countries and years, the ratio of Y/L and Y/K, i.e. K/L was greater than unity for the aggregated ICT capital variable, i.e. software, CT and IT capital. This implies that the productivity of labour grew faster than that of ICT capital. This finding holds true not only for the development of the ICT capital stock but also for the development of the overall capital stock (nor presented here).

Table 4: Growth Rates of Labour Productivity (Y/L), expressed in working hours

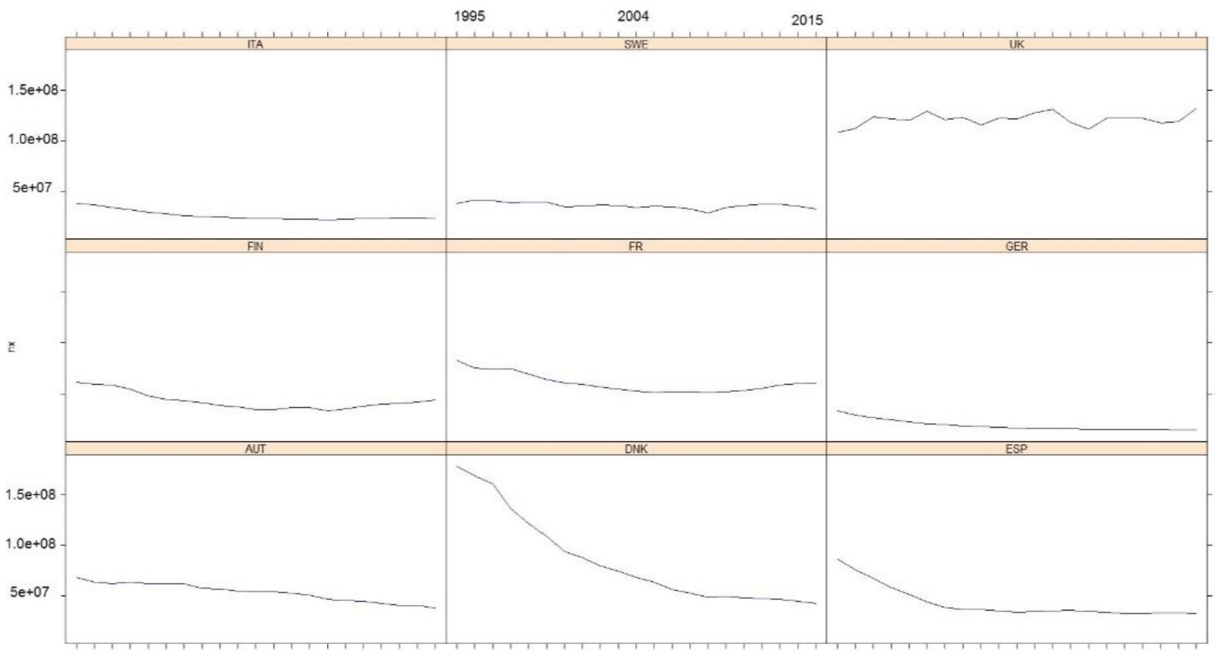
	1995-2015	1995-2004	2005-2015
Austria	0.023	0.041	0.021
Denmark	0.026	0.017	0.022
Spain	0.059	0.016	0.037
Finland	0.042	0.022	0.032
France	0.021	0.021	0.023
Germany	0.026	0.023	0.026
Italy	0.029	0.017	0.021
Sweden	0.029	0.024	0.027
UK	0.034	0.02	0.028

Source: EU KLEMS (9/2017) - own calculations

3.5. Robot Productivity Growth

Figure 5 and Table 5 describe the development of the average robot productivity (Y/R) - for the nine European countries considered between 1995 and 2015. For most countries and time periods, the annual growth rates are close to zero and negative, implying $\Delta\dot{Y} < \Delta\dot{R}$, thus leading to a moderate slowdown in the productivity growth of robots. From the top three robot-using countries, i.e., Germany, Italy and France, only the latter two mentioned countries experienced positive growth rates of robot productivity for the period between 2005 and 2015.

Figure 5: Robot Productivity (per Country)



Source: EU KLEMS (9/2017), IFR(2017) - own calculations

Table 5: Growth Rates of Robot Productivity (Y/R)

	1995-2015	1995-2004	2005-2015
Germany	-0.038	-0.065	-0.009
France	-0.015	-0.041	0.013
Spain	-0.045	-0.085	-0.005
Italy	-0.022	-0.044	0.001
UK	0.010	0.012	0.007
Denmark	-0.065	-0.083	-0.040
Finland	-0.016	-0.049	0.022
Sweden	-0.007	-0.005	-0.003

Source: EU KLEMS (9/2017), IFR(2017) - own calculations

4. Empirical Results

4.1.Research Question and Hypothesis

The empirical models serve to answer the question of whether the aspect of being a GPT elaborated under Section 2.1 can be empirically confirmed for industrial robots by using fixed effects panel estimation methods. This estimation approach was chosen as particularly for country groups, panel data analyses are a frequently employed estimation method and combine the advantages of both; times series (N=1) and cross-sectional analysis (T=1), which leads to a higher efficiency of the estimator (Hsiao, 2014).

Each model incorporates one of the main characteristics for considering an innovation a GPT, so that if at least M1, M2, M5 and M6 are fulfilled, robots can be characterized as a GPT. M3 and M4 serve as additional criteria for *pervasiveness* and *returns to scale* and, as such, appear to be less important for characterizing robots as GPTs than the four main criteria. For this paper, six different hypotheses are considered that include robots as an additional input for the production function of nine different European countries. The hypotheses are checked by way of different models for each hypothesis. All models account for disembodied technological change, where robots are included in the production function but are not attributed to a specific factor of input, i.e., capital or labour. As a robustness check, a separated ICT variable is used in order to check if either ‘Communication Equipment capital (referred to as CapCT)’, ‘Computing Equipment capital’ (referred to as CapIT) or ‘Software Capital’ (referred to as CapSoft) are relevant for the diffusion process of robot technology. Every estimator was corrected for underlying heteroscedasticity by using HC variance-covariance matrices. Different aspects of robots being GPTs are investigated:

i. M1: Robots have a significant, positive effect on labour productivity,

ii. M2: Robots show an increase in quality (Robot Task Intensity Index) which additionally raises labour productivity,

iii. M3: Robots have no significant effect on the division of labour (DoL) ,

iv. M4: Robots show significant returns to scale (Scherer−Approach),

v. M5: Effects from robots are significant and positive for the first sub-panel and significant for the second sub-panel. Comparing the size of the coefficients yields whether the productivity effects decrease or accumulate over time.

vi. M6: Robots lead to capital deepening, i.e., the significance of other capital variables increases after including industrial robots.

4.2. Empirical Models

For Models 1 – 6, the per capita production function, where each input variable is divided by the number of hours worked, takes the following principal form:

$$y_{it} = A_{it} \cdot r_{it}{}^{\alpha} \cdot CapCT_{it}{}^{\beta} \cdot CapIT_{it}{}^{\gamma} \cdot CapSoft_{it}{}^{\delta}$$

whereby y_t, $CapIT_{it}$, $CapCT_{it}$, and $CapSoft_{it}$ and r_{it} denote per capita output (measured in hours worked) and input in intensities of labour and different kinds of capital units and A_{it} measures Total Factor Productivity (TFP). As an ICT variable, the individual capital figures of CT and IT Capital were used and in accordance with Kromann et al. (2016) software is also included in the regression due to their line of argumentation, i.e., the aim is to use a measure of forms of capital that are not embodied in the robot measure. Software technologies of course are a relevant aspect of controlling industrial robots and thus can be seen as complementary innovations, which underlines the character of robots being a GPT. Software Capital contributes to the amount and complexity level of tasks that can be executed by robots. Software is measured in expenditures per annum and this is a very imprecise measure for the quality of the software. Interestingly, Software Capital is only weakly correlated with value-added ($r_{xy} \approx 0.124$), moderately correlated with labour productivity, measured in working hours ($r_{xy} \approx 0.3884$) and shows almost no correlation with CT and IT Capital ($r_{xy} \approx 0.037$ and $r_{xy} \approx -0.02$), respectively. Thus, including all three forms of capital is not expected to cause multicollinearity issues (Appendix II). For the sake of traceability from where the productivity gains originate, the three capital variables are used separately instead of the constructed ICT variable.

The regression model was conducted by using a diff-log approach to achieve stationary variables and simultaneously use elasticities for the sake of interpretation. TFP is captured via country and time fixed effects such that variables are allowed to vary systematically between countries. This way, the model accounts for different production technologies among those countries. Due to heteroscedasticity in the data, the regression models all make use of a HC estimator for the variance-covariance matrix to assure the validity of the estimator and significance levels.

4.2.1. M1: Industrial Robots and Labour Productivity

For M1, the regression model has the following specific form, wherein d_i and e_t denote country- and time specific fixed effects:

$$
\begin{aligned}
ln(y_{it}) - ln(y_{it-1}) \\
&= \alpha + \beta_1[ln(r_{it}) - ln(r_{it-1}) + \beta_2[ln(CapCT_{it}) - ln(CapCT_{it-1})] \\
&+ \beta_3[ln(CapITt) - ln(CapIT_{it-1})] + \beta_4[ln(CapSoft_{it}) - ln(CapSoft_{it})] \\
&+ d_i + e_t + u_{it}
\end{aligned}
$$

Table 6: M1 Regression Model (Results)

Diff (Log LP)	M1.1	M1.2	M1.3	M1.4
Diff(Log Robots / Log HEMPE)	0.179 (*)	0.266 (**)	0.246 (**)	0.262 (***)
Diff(Log CapCTtot / Log HEMPE)	-	-0.074	-0.05	-0.094 (***)
Diff(Log CapITtot / Log HEMPE)	-	-	0.118 (***)	0.054 (*)
Diff(Log CapSofttot / Log HEMPE)	-	-	-	0.07 (***)
Observations	188	188	188	188
Adj.RSq.	0.01	0.14	0.35	0.554

Source: Own calculations

Out of the four regressors, robots and Software Capital (each in per working hours) have the strongest impact on labour productivity. Increasing the operational stock of robots per hours worked by 3% leads on average to growth in labour productivity of roughly 1%. The effect of Software Capital equals approximately one third of the effect caused by robots. Communication Equipment Capital has a negative effect on labour productivity which is almost as high as the common positive contributions of Software and Computing Equipment on labour productivity growth. For the fully-specified model - despite the high significance levels - only roughly 55% of the variation in real valued-added can be explained by variations of robots, software and communication technology capital, each measured in working hours units.

4.2.2. M2: Quality Improvements of Industrial Robots: Robot Task Intensity Index (RTII)

The second model specification (M2) corrects for the fact that the data of robots used do not account for changes in the quality levels. Assuming that a robot installed in the year 1995 has on average the same contribution – ceteris paribus - to output or labour productivity as a robot installed in the year 2000 or the year of 2015 seems hardly plausible. This is an additional drawback of the IFR data as the homogenous perspective on different types of robots implicitly assumes the same contribution to economic outcome. As aggregates on a national level are considered, this aspect seems unavoidable even if different types of robots would have been accounted for in the IFR dataset. This issue is therefore not considered as problematic; the quality issue on the other hand seems highly relevant to capture process innovation dynamics. That robot usage starts in only a few applications while over time the number of tasks covered by robots is increasing is reported also by Carbonero, Ernst and Weber (Carbonero et al. 2018). The authors conclude that this "reflects one facet of technological improvement of automation, namely, the practical ability of carrying out more and more tasks" (p. 16). That can be seen as a sign of pervasiveness on a firm level. Acemoglu and Restrepo (2016) use the term "automation at the extensive margin" for technical change that fulfills more and more tasks in the production process. This stands in contrast to a technology that fulfills a given set of tasks with an increasing level of pace ('automation at the intensive margin') and thus raises the potential for economies of scope in production processes. While the rise of robots is well reported, their contribution at the 'extensive margin' needs further investigation. To overcome this limitation, a new index, the RTII, is introduced. It is constructed by using an indicator variable $\mathbb{I}$ that is 1 if a specific task (Appendix I) was executed in year t from at least one robot in country i and is zero otherwise. Next, the sum of all tasks for which robots were used was divided by the potential number of tasks for which robots can be operated (namely, 33). That way, the relative number of tasks (such as metal casting, plastic moulding, etc.) was taken into account to use a proxy for the diffusion process of robots across several tasks and industries (see Table 7 and Table 8). The RTII was calculated in two steps using the following procedures:

$$RTII = \exp(\eta_{it}), \text{ where}$$

$$\eta_{it} = \frac{1}{T}\sum_{j=1}^{T} t_j \cdot \mathbb{I}\{\Delta Robots_{it} \in \mathbb{R}^+\}$$

Table 7: Tasks Fulfilled by Robots (per Country)

Task. No. / Country	1	2	3	...	33	∑
Germany 1995	51375	20114	...	...	2401	151724
Germany 1996	60000	23826		...	2506	177494
⋮	⋮	⋮	⋮	⋮	⋮	⋮
France 1995	13274	6634	156	...	175	39647
⋮	⋮	⋮	⋮	⋮	⋮	⋮

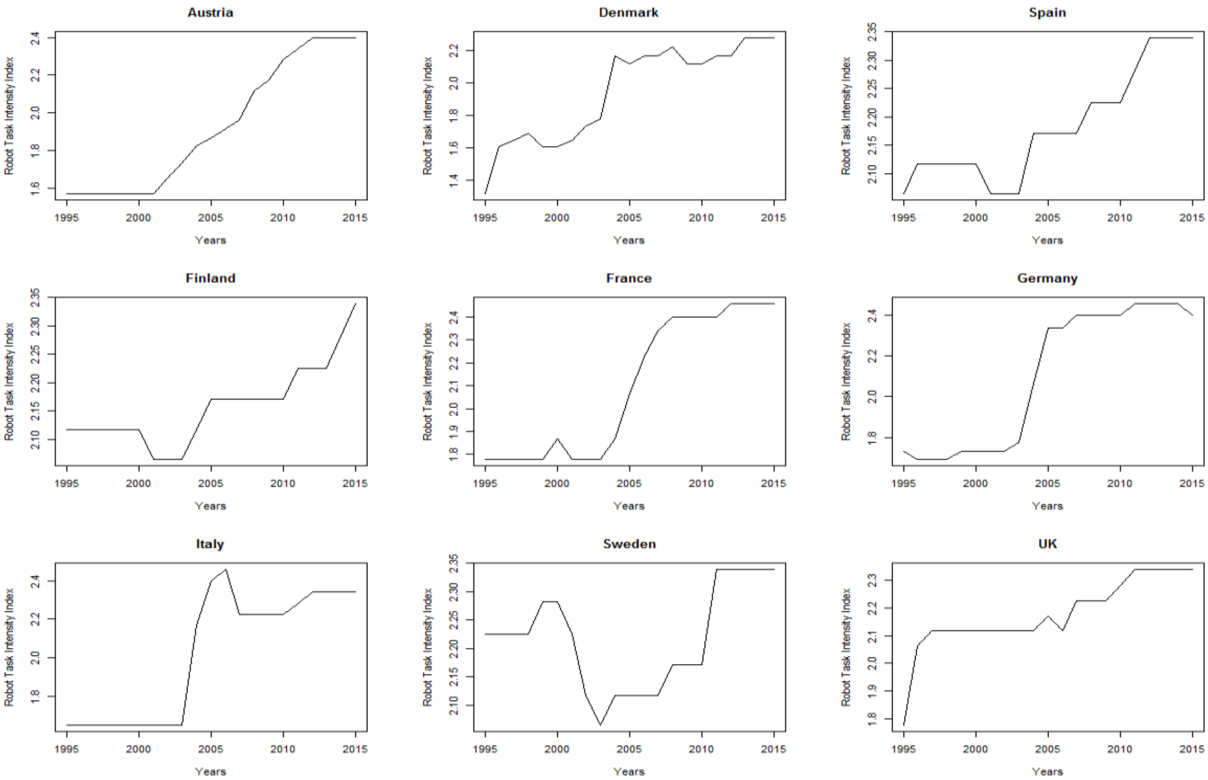
Source: Own representation

Table 8: Relative Shares of Tasks Fulfilled by Robots (η_{it})

Task. No. / Country	1	2	3	...	33	∑
Germany 1995	1/33	1/33	...	...	1/33	0.538
Germany 1996	1/33	1/33		...	1/33	0.513
⋮	⋮	⋮	⋮	⋮	⋮	⋮
France 1995	1/33	1/33	1/33	...	1/33	0.564
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Source: Own representation

Figure 6: RTII Results for all Countries in the Panel



Source: IFR(2017) – own calculations

The production function now becomes:

$$y_{it} = A_{it} \cdot (r_{it} \cdot RTII_{it})^{\alpha} \cdot CapCT_{it}{}^{\beta} \cdot CapIT_{it}{}^{\gamma} \cdot CapSoft_{it}{}^{\delta}.$$

Thus, the final regression model for M2 can be expressed as follows:

$$\ln(y_{it}) - \ln(y_{it-1}) =$$
$$\alpha + \beta_1[ln(RTII_{it} \times Robots_{it}) - ln(RTII_{it-1} \times Robots_{it-1})] + \beta_2[ln(CapCT_{it}) - ln(CapCT_{it-1})] + \beta_3[ln(CapIT_{it}) - ln(CapIT_{it-1})] + \beta_4[ln(CapSoft_{it}) - ln(CapSoft_{it-1})] + + d_i + e_t + u_{it}$$

Hence, fixed effects of country and time as well as the technical progress of robots - expressed in terms of the diversity of tasks that robots can perform - are considered which leads to a more realistic picture of how robots influence growth in labour productivity. On the downside, this measure can neither differentiate between the economic relevance of a specific task, nor capture task-changes – especially the fulfilling of new tasks - as categories are rigid in the IFR reporting nomenclature. The results in Table 9 demonstrate a highly significant improvement effect for robots. The RTII-related coefficient is the product of the RTII measure and the operational stocks of robots. It is highly significant and the size of the coefficient is almost 2.5 times larger than the IT and almost 4 times larger than the software coefficient. Both capital measures also have positive signs and thus serve as complements for robots. CT Capital, on the other hand, serves as a substitute for the other capital types, while the size of the economic effect lays between those of IT and Software Capital. Hence, only parts of the productivity gains caused by software and IT Capital are absorbed by CT Capital.

Table 9: M2 Regression Model (Results)

Diff (Log LP)	M2.1	M2.2	M2.3	M2.4
Diff(Log Robots / Log HEMPE x RTII)	0.125 (***)	0.191(*)	0.226 (***)	0.226 (***)
Diff(Log CapCTtot / Log HEMPE)		-0.061	-0.048	-0.083 (**)
Diff(Log CapITtot / Log HEMPE)			0.149 (***)	0.0911 (***)
Diff(Log CapSofttot / Log HEMPE)				0.065 (***)
Observations	188	188	188	188
Adj.RSq.	-0.07	0.019	0.351	0.519

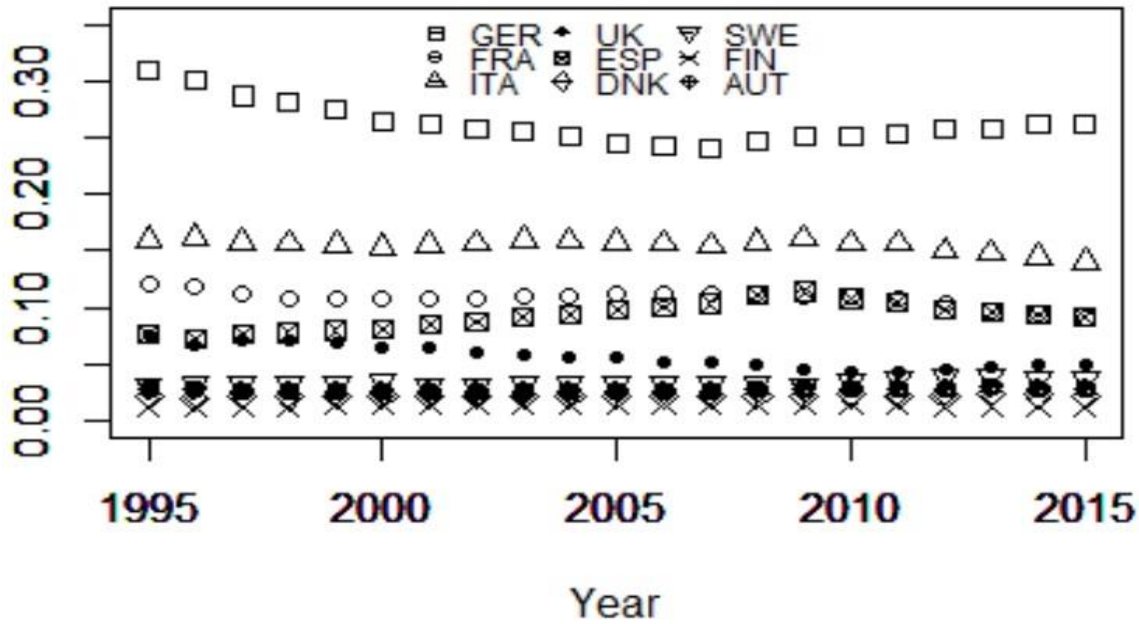
Source: Own calculations

Note: ***, ** and * display significance at the 1%, 5% and 10% level, respectively

4.2.3. M3: Industrial Robots and the Division of Labour (DoL)

In the third regression model, M3, the ratio of gross output to value-added serves as a regressand. This indirectly takes the different manufacturing shares of the countries into account (Figure 7). Like the manufacturing share, the ratio of gross output and value-added is always a positive number greater than unity, as a value of one would indicate no use of intermediates and thus no division of labour at all. A high level of the ratio corresponds to a country that makes a high use of the efficiency gains caused by DoL between and within countries. The idea behind the specification is that the relative size of the manufacturing sector to overall GDP is a powerful indicator for the economic competition profile of a country.

Figure 7: Manufacturing Shares of Value-added (per Country)



Source: EU KLEMS (2017) – own calculations

Naturally, besides the consideration of only the factors of production, even if innovative and economically-relevant such as robots, other aspects still do play a meaningful role, e.g., national growth strategies, the size of the home market, and the ability level of workers as well as historical aspects. Past innovations in one field raise the chance for future innovations, e.g., for disruptive innovations, subsequent innovations often follow in the same sector. For the establishment of electric car charging stations, the invention of ever more efficient batteries that increase the potential driving range are examples of such subsequent innovations. The measure thus gives rise to the question of how strong the effects of current inputs are for the competitiveness of the European manufacturing industry. The underlying structure of the production model M3 is:

$$DoL = \frac{\frac{GO_{manuf}}{VA_{manuf}}}{\frac{GO_{tot}}{VA_{tot}}} \times \frac{HEMPE_{manuf}}{HEMPE_{tot}} = A_{it} \cdot CapIT_{it}^{\alpha} \cdot CapCT^{\beta} \cdot CapSoft^{\gamma} \cdot r_{it}^{\delta}.$$

Thus, the final regression model for M3 can be expressed as follows:

$$\begin{aligned}
&\ln(DoL_{it}) - \ln(DoL_{it-1}) \\
&\qquad = \alpha + \beta_1[\ln(r_{it}) - \ln(r_{it-1})] + \beta_2[\ln(CapCT_{it}) - \ln(CapCT_{it-1})] \\
&\qquad + \beta_3[\ln(CapIT_{it}) - \ln(CapIT_{it-1})] + \beta_4[\ln(CapSoft_{it}) - \ln(CapSoft_{it-1})] \\
&\qquad + +d_i + e_t + u_{it}
\end{aligned}$$

With DoL as a measure of the division of labour, one can distinguish between whether an economy uses only relatively few intermediates and concentrates exclusively on building final goods. In such cases, supply- and demand-side shocks are more difficult to absorb. This means that for countries that make lower use of labour division, higher efforts and expenditures are necessary when combatting the negative results of a shock. The higher the degree of DoL of an economy is, the more relative weight it has in each industry compared to other states and the more it can make use of the productivity gains caused by the division of labour. This then results in a higher level of competitiveness such that shocks will only have a temporary effect on the outcome level of the overall economy (Carvalho and Tahbaz-Salehi, 2019). To shed light on the question of whether robots not only increase labour productivity but also improve the level of the DoL, M2 is estimated again, using DoL as the dependent variable, resulting in model M3. More precisely, the relative level of DoL of the manufacturing industry (DoL manuf) divided by the level of DoL of total industries (DoL tot) - is used. This indicator measures the relative importance of total robot intensity for the relative level of DoL. Due to the aspect that DoL represents a ratio, the manufacturing-total industries ratios are used as regressors, e.g., the amount of manufacturing robots divided by the total amount of robots used in country i. This ratio is then multiplied by the ratio of total working hours and manufacturing working hours. This has been done in order to achieve results, which correspond to the model specifications of the former models. A modification was necessary for the robot share as using logarithms requires positive values for operational stock ratios which was not the case for countries who installed robots in manufacturing after 1995 (Denmark in 1996 and Austria in 2002). For these cases, the constant number ‘one’ was added to the stocks which had no negative drawback either mathematically or economically. The first argument is true since mathematically $ln(1 + r) \approx r$ holds for small r and the second argument holds since no installations - neither in the panel nor in any real-world production plant - ever start with a single robot so that ln(1) = 0 leads to no bias in the operational stocks. RTII was not considered here as the task intensity of robots does not seem to be crucial for the DoL output measure as the values for the DoL lie between 1.16 (UK in 2000) and 2.28 (Spain in 2007). In 2015, Italy (2.1.), France (1.96) and Germany (1.41) were the economies that made use of the DoL most extensively. The modus, with a frequency of 91, is located at the value of two.

In the regression model, the level of DoL is only weakly correlated with the size of the economy. Industrial robots show no significant effect on the DoL at all. This suggests that they have no effect on the degree of DoL for the European economies under consideration. IT Capital per hours worked drives the speed of economic integration, i.e., an increase of IT Capital per working hour by 10%, increases the DoL by roughly 1.2%. The effect is significant at the 10%

level. CT Capital shows an effect in the opposite direction: An increase in CT Capital by 10% decreases the DoL by 1.2%. Thus, IT Capital leads to a higher DoL level of the manufacturing sector compared to other sectors, while CT Capital fosters innovation diffusion and thus leads to a less dominant share of manufacturing in the DoL variable. CT Capital and Software Capital otherwise do have a significant influence on the level of the DoL, while IT Capital does not. Although this finding corresponds to the theoretical considerations of diffusion processes, it does so in an opposite way. As CT Capital is more specific and more heterogeneous on a firm level, CT Capital would be expected to lead to competitive advantages. IT Capital on the other hand has far diffused in the past decades and already caused increases in productivity but not in the level of competitiveness as the speed of diffusion hindered even temporary monopolistic revenues. Nonetheless, the explanatory power of the model is indisputably low.

Table 10: M3 Regression Model (Results)

Diff (Log LP)	M3.1	M3.2	M3.3	M3.4
Diff(Log (1+Rel Robots pch))	-1.23	-1.41	-1.35(*)	-0.33
Diff(Log(Rel CapCT pch))		0.738	0.73	0.894
Diff(Log(Rel CapIT pch))			-0.28	1.502
Diff(Log(Rel CapSoft pch))				-1.9
Observations	188	188	188	188
Adj.RSq.	-0.16	-0.16	-0.16	-0.11

Source: Own calculations

Note: ***, ** and * display significance at the 1%, 5% and 10% level, respectively

As the regression output table shows (Table 10), the level of DoL is not influenced by either the per capita robot stocks or one of the other factors of production. The process of dividing labour inside a firm is a binding prerequisite for productivity gains to spread throughout the economy. Therefore, this investigation might deliver different results when firm level data is used. At a macro level for the nine European countries in question, an enhanced DoL cannot (yet) be observed for any of the factors of production.

4.2.4. M4: Industrial Robots, Returns to Scale and Labour Productivity

After considering the most relevant aspects via M1-M3, the opportunity arises to quantify a more sophisticated relationship between the robots employed and labour productivity. Following the line of argumentation of Scherer (1989), innovations may not be sufficiently accounted for in a purely linear representation. In order to develop a proxy for the long-term relationship, that corresponds to the second derivative $\frac{\delta^2 Y}{\delta r^2}$, a quadratic term can be included to estimate an additional increase in the factor of production contributing to output growth. Scherer (1989:231f.) offers the following interpretation of the quadratic coefficient:

i) If the regression intercept is zero and the quadratic term is insignificantly different from zero, the size of the beta coefficients show the level of returns to scale,

ii) if the quadratic term is significantly negative (and the linear term is significantly positive), decreasing returns to scale exist and

iii) if the quadratic term is significantly positive (and the linear term is significantly positive), increasing returns to scale exist.

Therefore, in line with Scherer, an additional simple panel regression including time and country fixed effects between output and robots is considered, i.e.,

$$Output \approx \alpha + \beta_1\ Robots_{it} + \ \beta_2 Robots_{it}^2\ + d_i + e_t + u_{it}$$

to analyze the functional form of the robots and to check whether the intercept is significantly different from zero. Due to perfect multicollinearity, the regression had to be run successively, first with robots and then with robots squared as single regressor. The results are presented in Table 11. The squared robots is calculated as Robots pch Sq=Robots^2/HEMPE. Labour productivity is considered as a dependent variable. The production function for M4 takes the following form:

$$y_{it}\ =\ A_{it}\ \cdot\ CapIT_{it}\ \cdot\ CapCT_{it}\ \cdot\ CapSoft_{it}\ \cdot\ r_{it}^2$$

Thus, the final regression model for M4 can be expressed as follows:

$$\begin{aligned}\ln(y_{it}) - ln(y_{it-1}) \\ &= \alpha + \beta_1[\ln(CapCT_{it}) - \ln(CapCT_{it-1})] + \beta_2[\ln(CapIT_{it})] - \ln\ (CapIT_{it-1})] \\ &+ \beta_3\ [\ln\ (CapSoft_{it}) - \ln\ (CapSoft_{it-1})] + \beta_4[\ln(r_{it}) - \ln\ (r_{it-1})] +\ di\ +\ et \\ &+\ uit\end{aligned}$$

Table 11: Scherer Specification Models

	Intercept	Coefficient	Adj. R2
Diff Log VA _ Diff Log Robots P-Values	0 -	0.842(***) < 2.2e-16	0.809 -
Diff Log VA _ Diff Log Robots Sq. P-Values	0 -	0.421 (***) < 2.2e-16	0.809 -
Diff Log Labprod _ Diff Log Robots P-Values	0 -	0.1792 0.099 (*)	0.01 -

Diff Log Labprod_ Diff Log Robots Sq P-Values	0 -	-0.01 0.739	-0.17 -

Source: Own calculations

Note: ***, ** and * display significance at the 1%, 5% and 10% level, respectively

The differences of the logged robots and robots per working hours have a significant positive effect on value-added and labour productivity. The squared robots have a positive significant effect on changes in value-added (increasing returns to scale). This does not hold for labour productivity where no returns to scale are at hand. For the subsequent regression models, only the Robots pch Sq (s.a.) is used.

Table 12: M4 Regression Model (Results)

Diff (Log LP)	M4.1	M4.2	M4.3	M4.4
Diff(Log (Robots2/Log HEMPE))	-0.012	-0.007	-0.0042	0.053 (**)
Diff(Log (CapCT/LogHEMPE))		-0.013	0.004	-0.073
Diff(Log (CapIT / Log HEMPE)			0.13(*)	0.048
Diff(Log CapSoft/ Log HEMPE)				0.095 (***)
Observations	188	188	188	188
Adj.RSq.	-0.177	-0.179	0.075	0.312

Source: Own calculations

Note: ***, ** and * display significance at the 1%, 5% and 10% level, respectively

The significance of squared robots could be confirmed only by adding Software Capital as an additional regressor variable. Thus, Software Capital and robots work as gross-complements in output creation. This relationship is non-linear: With an additional increase of robots (Squared Robots) the level of Software Capital used decreases. That way, the intuition of increasing returns to scale from Table 11 concerning robot stocks can also be confirmed for the relationship between robot intensity and labour productivity in the multiple panel regression model. With a 1% increase in squared robots, labour productivity increases in average by 0.05%. Nevertheless, as this effect is roughly 1/4 of the former measured effect from robots on labour productivity (Table 6, Table 9), the indication of increasing returns to scale is limited.

4.2.5. M5: Time Effects from Industrial Robots on Labour Productivity

That robots contribute to labour productivity according to the year of first installation is a plausible assumption taking into account that the quality of robots is improving over time. If the technical progress is strong enough, this might result in a change of the scale level of the macroeconomic production function. To check for this assumption, the panel was split into two almost equally sized sub-panels, one sub-panel covering the period from 1995 to 2004 and the other sub-panel the period from 2005 to 2015. Even though the year 2005 was politically important - as two of the EU founding countries, namely Netherlands and France, voted against the proposed EU constitution[2], the main reason for splitting the data in 2005 was the desired symmetry in the two sub-panels. This procedure was also chosen by Jungmittag and Pesole (2019). There are two theoretical lines of argumentation here: As robot stocks increase over time, robots installed later may suffer from the law of diminishing returns to scale and therefore show lower or even no influence on productivity. On the other hand, latterly installed robots embody a higher level of current technical progress and thus could lead to higher productivity gains than those robots installed earlier. In the same direction, goes the argument that robots - because they are a GPT - need some time to spread their productive power over the economy, especially if robots reveal their full economic impact after accumulation over time.

Table 13: M5 Regression Model (Results) - Time Split (1995-2004)

Diff (Log LP)	M5.1	M5.2	M5.3	M5.4
Diff Log LP	0.075 (***)	0.11 (***)	0.136 (***)	0.139 (***)
Diff(Log (CapCTtot / LogHEMPE))		-0.02 (**)	-0.04 (***)	-0.077 (***)
Diff(Log (CapITtot / Log HEMPE)			0.023 (*)	0.063 (***)
Diff(Log CapSofttot / Log HEMPE)				0.09 (***)
Observations	89	89	89	89
Adj.RSq.	-0.1	-0.01	0.1	0.581

Source: Own calculations

Note: ***, ** and * display significance at the 1%, 5% and 10% level, respectively

Table 14: M5 Regression Model (Results) - Time Split (2005-2015)

Diff (Log LP)	M5.1	M5.2	M5.3	M5.4
Diff Log LP	0.076 (***)	0.02 (***)	0.03 (***)	0.125 (***)
Diff(Log(CapCTtot / LogHEMPE))		0.03 (***)	0.025 (***)	-0.06 (***)

[2] Some theoretical explanations for this decision are discussed in Binzer Hobolt and Brouard (2011).

Diff(Log (CapITtot / Log HEMPE)			0.008 (***)	-0.12 (***)
Diff(Log CapSofttot / Log HEMPE)				0.192 (***)
Observations	98	98	98	98
Adj.RSq.	0	0.1	0.1	0.66

Source: Own calculations

Note: ***, ** and * display significance at the 1%, 5% and 10% level, respectively

The regression results of M5 indicate that the effects from robots on labour productivity are lower for the second sub-panel than it was for the first sub-panel. For the first 10 years of the panel, there was a highly significant effect from robots in the range of 0.139, while for the final 11 years there is again a highly significant effect but the coefficient is roughly 10% smaller. These results contradict the idea of robots being a GPT as -by interpretation of the regression results - it is unlikely that the peak of productivity caused by robots is still to come.

4.2.6. M6: Capital-Augmentation vs. Capital-Deepening

Finally, and in order to test the hypothesis that robots lead to capital-augmenting technical change, a step-wise multivariate regression is conducted where robots are added to the model as the final variable. The output results are reported in Table 15.

The results show that robots behave as a substitute for CT Capital (negative sign of the coefficient) but as a complement for Software and IT Capital. The answer to the question of whether robots lead to capital augmentation might be given by comparing the overall effect from capital (0.101), which is lower than for the model specification without robots. Therefore, there is a tendency for capital deepening - when robots are attributed to capital goods - but no tendency indicating capital-augmenting technical progress caused by robots.

Table 15: M6 Regression Model (Results)

Diff (Log LP)	M6.1	M6.2	M6.3	M6.4
Diff Log LP	0.174 (***)	0.002	-0.032(**)	-0.09
Diff(Log(CapCTtot/LogHEMPE))		0.13 (*)	0.073	0.05 (*)
Diff(Log (CapITtot / Log HEMPE)			0.065 (*)	0.07 (***)
Diff(Log CapSofttot/ Log HEMPE)				0.26 (***)
Observations	189	189	189	189
Adj.RSq.	0.189	0.08	0.246	0.55

Source: Own calculations

Note: ***, ** and * display significance at the 1%, 5% and 10% level, respectively

5. Conclusion

The scope of the present paper is to answer the question of whether industrial robots are a GPT. To answer this question on a macro level, a panel data analysis for nine European countries was conducted to test different characteristics of a GPT according to the literature. Each of the six research questions could be linked to a specific regression model and the coefficients tend in the expected directions. Firstly, robots increase labour productivity (M1) but have no effect on the level of Division of Labour (DoL) (M3). The latter point reflects the idea that a GPT does not lead to a concentration in some industries but evenly spreads its productivity gains throughout the economy. These results have to be interpreted cautiously because the overall explanatory power of the model was very low, indicating that the output measure is not affected by any of the regressors. Still, both results show that pervasiveness is (already) caused by robots. Additionally, model M2 demonstrated that robots are not only an example of an innovative input, but that robots themselves are inherently driven by technical progress. By implementing an innovative, novel measure of technical progress (the Robot Task Intensity Index - RTII) within the operational stock of robots, the technical improving nature of robots is demonstrated (M2). This improvement effect remains stable even when Software Capital is included in the regression model. Interestingly, Software Capital could also be identified as an enhancing force increasing returns to scale from robots. The Scherer approach (M4) showed that there are returns to scale for the full specified model, i.e., using all types of capital. For the purpose of defining robots as GPTs, this finding is sufficient as, as the discussion in Section 2 indicates the existence of high returns to scale speak against technologies being considered a GPT. Nonetheless, the effect seems moderate which corresponds to the finding in the time-split regression model (M5). It was shown that productivity gains from robots slowed down for the time period between 2005 and 2015 in contrast to the period between 1995 and 2004. This particular finding is a clear indication in support of the idea that robots can already be considered a GPT. Finally, yet importantly, robots give rise to innovational complementarities as they lead to capital deepening but not to capital augmentation for the process of labour productivity creation (M6).

Overall, none of the six hypotheses developed in order to investigate specific characteristics of a GPT on a macro level could be rejected. Although the results speak in favour of robots being a GPT, several aspects have to be mentioned critically: As a macro perspective was chosen, the appearance and size of potential spillovers from robots could not explicitly be accounted for, which is a crucial part of the understanding of a GPT. Additionally, it was not possible to distinguish between the types of returns to scale (i.e., whether due to Dynamic vs. Static Externalities). Hence, in future research, the relationship between a GPT and industrial robots can be elaborated in more detail, for example by using firm-level data, or by considering trade relations among the most robotized European countries. Nevertheless, the study revealed the impact that robots have on the development of labour productivity. For policymakers, the combined enhancement of modern robot technologies as well as sophisticated software applications, which serve as complementary innovations to industrial robots, appear to be effective tools to generate growth in outcome and labour productivity among European countries and thus to counteract the productivity slowdown.

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Appendix

Table 16: Task Categories by Field of Application

No. task	Id. No.	Task-Description
1	111	Metal casting
2	112	Plastic moulding
3	113	Stamping forging, bending
4	114	Handling operations at machine tools
5	115	Machine tending for other processes
6	116	Measurement, inspection, testing
7	117	Palletizing
8	118	Packaging, picking, placing
9	119	Material handling
10	120	Handling operations unspecified
11	161	Arc welding
12	162	Spot welding
13	163	Laser welding
14	164	other welding
15	165	Soldering
16	166	Welding unspecified
17	171	Painting and enameling
18	172	Application of adhesive, sealing material
19	179	Others dispensing/spraying
20	180	Dispensing unspecified
21	191	Laser cutting
22	192	Water jet cutting
23	193	Mechanical cutting/grinding/deburring
24	198	Other processing
25	199	Processing unspecified
26	201	Assembling
27	203	Disassembling
28	209	Assembling unspecified
29	901	Cleanroom for FPD
30	902	Cleanroom for semiconductors
31	903	Cleanroom for others
32	905	Others
33	999	Unspecified

Source: IFR (2017:41)

Table 17: Correlation Matrix

	Real VA	Robots	HEMPE	CapCT	CapIT	CapSoft	η
Real VA	1						
Robots	0.79	1					
HEMPE	0.89	0.56	1				
CapCT	0.67	**0.92**	0.41	1			
CapIT	0.86	0.77	0.64	0.65	1		
CapSoft	0.45	0.58	0.12	0.58	0.65	1	
RTII	0.53	0.72	0.37	0.74	0.35	0.32	1

Source: Own calculations

Note: All Values are reported in diff logs.

Table 18: Correlation Matrix

	Real VA	Robots	HEMPE	CapCT	CapIT	CapSoft	η
Real VA	1						
Robots	0.87	1					
HEMPE	0.56	0.76	1				
CapCT	0.86	0.72	0.46	1			
CapIT	0.86	0.47	0.52	0.57	1		
CapSoft	0.68	0.63	0.7	0.65	**0.96**	1	
RTII	0.6	0.68	0.56	0.39	0.29	0.155	1

Source: Own calculations

Note: Significance levels are stated in parentheses.
Bolded value indicates a potential multicollinearity issue as the variance inflation factor ($\frac{R^2}{1-R^2}$) is greater than ten (Hair et al., 2014).

All Values are reported in diff logs per capita hours worked.

Table 19: Unit Root CADF Tests-Results (Intercept), α=5%

	Real VA pch	VA/GO	Robots pch	CapCT pch	CapIT pch	CapSoft pch	RTII
P-Value	0.001	0.349	0.22	0.14	2e-6	0.31	0.0022
Stationarity	Yes	No	No	No	No	No	Yes

Source: Own calculations

Table 20: Wooldridge's test for Serial Correlation in FE panels Tests-Results, α=5%

	M1	M2	M3	M4	M5.1	M5.2	M6
P-Value	0.00015	0.0025	9.3e-08	0 .059	0.668	0 .999	0.00015
Stationarity	No	No	No	Yes	Yes	Yes	No

Source: Own calculations

Table 21: Pesaran Tests- of Cross-Sectional Dependence, α=5%

	Real VA pch	VA/GO	Robots pch	CapCT pch	CapIT pch	CapSoft pch	RTII
P-Value	< 2.2e-16	<2.2e-16	< 2.2e-16	<2.2e16	<2.2e-16	<2.2e-16	<2.2e-16
Independ.	No	No	No	No	No	No	No

Source: Own calculations

Table 22: Breusch Pagan Heteroscedasticity Test-Results, α=5%

	M1	M2	M3	M4	M5.1	M5.2	M6
P-Value	5.7e-8	9.2e-11	0.003	<2.2e -16	0.34	0.08	<5.7e-8
Heterosce dasticity	Yes	Yes	Yes	Yes	No	No	Yes

Source: Own calculations

Table 23: Hausman Test. α=5%

	M1	M2	M3	M4	M5.1	M5.2	M6
P-Value	0.995	0.999	0.977	0.991	<7.9e-13	<2.2e-16	0.995
FE prior	No	No	No	No	Yes	Yes	No

Note: If either heteroscedasticity or serial correlation is present, the variances of the FE and RE estimators are not valid and the corresponding Hausman test statistic is inappropriate (Baltagi, 2005). This was avoided by using solely stationary variables, which provided uncorrelated errors. For both M5 models only time effects were considered as otherwise the degrees of freedom were too low.

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