Robots at work: recent evidence with new data

Derick Almeida
Ph.D. Student at Faculty of Economics, University of Coimbra

Tiago Miguel Guterres Neves Sequeira
University of Coimbra, Centre for Business and Economics Research, CeBER and Faculty of Economics

CeBER Working Papers
No. 4 / 2022

CeBER is funded by the Foundation for Science and Technology, I.P.

Robots at work: recent evidence with new data§

Derick Almeida

Univ Coimbra, CeBER, Faculty of Economics*

Tiago Neves Sequeira

Univ Coimbra, CeBER, Faculty of Economics*

Abstract

We reassess the relationship between robotization and the growth in productivity in the light of new data and methods. We discover that the effect of robot density in the growth productivity substantially decreased in the post-2008 crisis period. Moreover, in this more recent period, the less strong positive effect of robot density in the growth of productivity is mostly derived from negative effect of hours worked in productivity, showing that robots lost part of their capacity to increase productivity through value-added. By means of quantile regression, we also learn that the effect of robots on labor productivity is stronger for low productivity sectors and that in the most recent period, the effect of robotization in all sectors, felt significantly throughout the distribution, with special emphasis in the most productive sectors. This highlights one of the possible sources of the secular stagnation in the era of robotization and artificial intelligence technologies.

Keywords: Robots, Robotization, Labor Productivity, Productivity Growth, Stagnation
JEL codes: E23, J23, 030

---

§ This paper is intended to be the first of the PhD thesis to be submitted as partial requirement to obtaining the doctor degree in Economics by the University of Coimbra by Derick Almeida. The thesis is supervised by Tiago Neves Sequeira. This research benefited from support of the FCT [2020.07402.BD] and from funds from CeBER which is financed by Portuguese public funds through FCT—Fundação para a Ciência e a Tecnologia, I.P., in the framework of the project with reference UIDB/05037/2020. This paper benefitted from presentations during the PhD program, in CeBER research seminar, and in the ICEA Conference *The Wealth of Nations in Pos-Covid Era* (Univ. Milan) and discussions with several colleagues. The usual disclaimer applies. The codes and non-proprietary data used for obtaining the results are available upon request (after the publication of the article).
***** Univ Coimbra, CeBER, Faculty of Economics. Avenida Dias da Silva, 165, Coimbra, Portugal. Email for Derick Almeida: drckalmeida@gmail.com. Email for Tiago Sequeira: tiago.n.sequeira@fe.uc.pt.

I. Introduction

The defining feature of robotization (e.g. Acemoglu, 2018) is its capacity to revolutionize the economy across the industries' boards and not just one specific industry, being classified as a General Purpose Technology (GPT). The importance to research the structural effects of robots in the economy is to contribute to a continuum of studies regarding the relationship between technological progress and the productivity growth. This course of investigation has taken a prominent role in economic research ever since the seminal work of Solow (1956) showed that the steady-state equilibrium growth of income *per capita* depends ultimately on the rate of technological advancement. Since then, economists developed models to understand the fundamental source of technological improvement where the research of Kenneth Arrow, Paul Romer, Robert Lucas, Phillip Aghion and Daron Acemoglu forged an understanding of the mechanics of endogenous growth.

Robots and sophisticated computer programs with human-like skills are no longer characters of a 20th century dystopian science fiction novel. They are already a reality translated into 3 million industrial robots working around the world at this moment in sectors as diverse as metal, chemicals and automotive production, according to the International Federation of Robots (IFR). In the past half decade, more than 300.000 robots have been deployed every year to the existing operational stock with a 6% average annual growth rate projected for the coming years until 2024. At that pace, the flow of new robots to economic activities doubles every 12 years. This technological movement is so intense, wide ranging and potentially disruptive that many authors insert it in a context of a 4th industrial revolution (Schwab, 2016).

Even though the numbers are showing increased investment in automation and technological innovations on this front are flourishing every year, there exists some hesitation from the part of economists to accept that these rapid transformations can spur consistent economic growth over time, much in the same fashion as the wave of Information and Communication Technologies (ICT) stopped delivering its promises of economic growth after the early 2000's (Gordon, 2015; Sequeira et al., 2018).

The widespread and increasing use of robots in economic production, particularly but not exclusively in manufacturing, calls for a deeper understanding of how it has affected the dynamics of important economic variables, especially labor productivity, in the past 20 years. Empirical tests on the impacts of robotization in the economy are quite recent in the literature. One of the most important results comes from Graetz & Michaels (2018) that propose a task-based model based on Acemoglu and Restrepo (2018) and Zeira (1998) to understand the causal relationship between robot density, labor productivity and the skill composition of the employed population. The authors test an econometric model in which labor productivity growth is a function of robot density and find that an increase in robot density (robots per million hours worked) increases labor productivity growth and get no statistically significant effects of robot use over employment for country-industry pairs analyzed. A noteworthy point is that the authors use a task replaceability index as an instrument for robot density in order to solve potential endogeneity problems coming from the fact that higher labor productivity can also cause higher robot densification (Graetz & Michaels, 2018) through the channel of higher wages and increased cost of labor.

On a theoretical side, Acemoglu & Restrepo (2020) develop a task-based model with heterogenous labor and can decompose the effects of robotization on labor productivity in three distinct sources: substitution, productivity and reinstatement effects. The authors show that labor productivity growth can be either positive or negative in the face of an automation shock, i.e. an increase in the number of tasks performed by machines, depending on how these forces balance. Acemoglu & Restrepo (2020) argue that if the substitution effect is high relative to the other two effects, meaning that machines are substituting labor rather faster than increasing the productivity of the system and creating new labor-intensive tasks, labor productivity growth can be severely hit and even enter negative territory.

Important theoretical implications concern the effect of automation, not only on average labor productivity and labor demand but also on labor productivity of different skill-groups of workers. When we consider low-skill and high-skill labor in the model, these effects also play an important role and create important asymmetric effects of robotization on each group's growth rate of productivity. The kind of robotic automation that has been observed in recent times (Autor et al., 2020; Graetz & Michaels, 2018; Battisti et al., 2021) points in the direction of unskilled automation, a phenomenon that, when seen through the model with heterogenous labor of Acemoglu & Restrepo, either creates or intensifies the dispersion of labor productivity, with higher productivity individuals showing benefiting from automation while low productivity individuals lose their productive post.

Recent discussions around the topic of the *secular stagnation*, roughly summarized as a situation of chronic low productivity growth equilibrium, point toward a rather bleak scenario in which recent technological improvements, namely Information and Communications Technologies (ICT) , Robotics and Artificial Intelligence, are not going to speed up value-added per hour worked as much as previous revolutionary 19th and 20th century technologies, such as the steam engine and electricity (Gordon, 2015; Sequeira et al., 2018). If verified empirically, this potential decreasing returns to scale of (robotization) technology in the very long run could obstruct an important avenue for sustained labor productivity growth by making the substitution effect of robotization superimpose on the other two beneficial effects, i.e. the productivity and reinstatement effects.

Considering earlier developments in the field, the main contribution of this paper rests in its novel results brought by newly available data from the International Federation of Robotics (IFR) and the EUKLEMS. We extend Graetz & Michaels (2018) empirical analysis of the effects of robotization on labor productivity to the period 1997-2017, first approximating the results of their paper in the first part of the sample (1997-2007) and then applying the same methodology to the second part of the sample (2008-2017) to conduct a comparative analysis between the results of the effects of modern automation on labor productivity in the two periods. We corroborate Graetz & Michaels (2018) results and additionally discover that the effects of higher robot intensity over labor productivity falls greatly in the last 10 years, from 3.4-6.4 percentage points to 1.2-2.3 percentage points in the baseline scenario where we normalize per hour worked variables by total hours worked by person engaged. In both cases, the lower bound is given by the estimates of the model without country fixed-effects and without instrumental variable, while the upper bound of the estimates is related to the model with country fixed-effects and instrumental variable. In the case where variables are normalized by total hours worked by employees, the effects fall from 4.1-7.9 percentage points between 1997-2007 to 2.3-3.6 percentage points between 2008-2017. We also find evidence that the increase in labor productivity in recent years is not only lower than in the first sample, but has been driven by a strong slowdown in robot's capacity to increase value-added growth while still being an important source of labor-hour substitution. In the more robust scenarios, where we used the Replaceability Index as an instrumental variable and country fixed-effects, the effect of robots on value-added growth falls by as much as 78% between the two subsamples while the effect of robots on hours worked growth increases by 33% in the same comparison. This result may uncover a shifting bias from value-added creation of robotic technology to a more labor-hours substitution bias. We encounter this pattern independently of the measure we use of hours worked.

This paper is organized in the following way. In section II, we describe the methodology and the database we use to estimate the different models that relate robotization with labor productivity growth. In section III, we approximate the results of Graetz & Michaels (2018), from here onwards referred to as GM, for the period 1997-2007. In section IV, we expand the analysis analysis to the period 1997-2017, looking with particular interest to the period of 2008-2017 and the different pattern that emerges in the relationship between labor productivity growth and robotization. In section V, motivated by the theoretical literature that relates robotic automation to heterogenous labor productivity, we broaden our empirical framework to incorporate quantile regressions to identify possible asymmetric effects of robotization on the conditional distribution of labor productivity growth. Finally, in Section VI we write the concluding remarks.

II. Methodology and data description

For this paper, we consider 14 developed countries (Austria, Czech Republic, Denmark, Finland, Germany, Great Britain, Greece, Italy, France, Lithuania, Netherlands, Spain, Sweden, United States) and 13 ISIC Rev. 4 industries (Agriculture; Mining; Food products; Textiles; Wood, paper and printing; Chemicals, Rubber & Plastics; Metal; Electronics; Machinery; Automotive; Utilities; Construction and Education) in the sample. The time range considered is from 1997 to 2017.

Even though we work with the same database sources, our sample slightly differs from the benchmark (GM) in three different dimensions: countries, industries, and time horizon. Due to methodological changes in the EUKLEMS database, the availability of information for country-industry pairs and the way variables are calculated changed when compared to GM's database. An important factor is that the EUKLEMS new database under *The Vienna Institute for International Economic Studies* (Stehrer, 2021) is not methodologically consistent with that used by GM (Timmer, et al. 2007) and, therefore, cannot be used as a direct extension to fill in possible gaps. This results in some loss of previous information, especially in years prior to 1995, and comparability. Nonetheless, of the 14 countries that we consider in the original sample, 11 match those used by GM. In terms of the sectors analyzed, we use a rather close classification to GM's, which follows the ISIC Rev. 4 standard but with some slight variation in the level of aggregation of some industries, e.g. Wood and Paper and Chemicals,[1] but with no fundamental difference as it will be clear in the comparison of our descriptive statistics and other results. In

[1] Due to the necessary matching with the new version of the EUKLEMS, in our sample, we aggregate Wood products & Paper in one industry as well as Chemicals & Other Mineral, while GM treats these two industries as four separate sectors (Wood products, Paper, Chemicals and Other Mineral). The rest of the sectors are treated in the same way as in GM.

the case of the time horizon and the initial period of the sample, it is important to note why our work does not consider data before 1997 whereas GM use available information since 1993. The methodological changes of the newest version of EUKLEMS exclude from the database information on Real Value Added and Total Hours Worked for the US economy before 1997. Since the country is an important market for robots, it is crucial that it is included in the database.

2.1.Variables and data sources

The main questions this research attempts to answer is how the impact of increased robotization, understood as deepening in the number of robots per million hours worked, on labor productivity, has evolved in last two decades, especially when comparing the first 10 years (1997-2007) to the last 10 years of the sample (2008-2017). Following this analysis, we try to assess possible asymmetric effects by calculating how much the use of robots in a range of industries affect different parts of the conditional labor productivity distribution. We arrive at those results by applying Machado & Santos Silva's (2021) Method of Moments Quantile Estimator.

Bellow, we provide the definition of dependent as well explanatory variables. For the following exposition, the index sets I, $\mathcal{J}$ *and* $\mathcal{T}$ represent the universe of industries, countries and time periods, respectively.

When calculating the main variables used in our model, we follow closely GM (2018). Labor productivity is obtained as the ratio of constant prices gross value added by total hours worked for each industry-country pair converted to dollars (US$) by yearly nominal exchange rates.

$$LP_{ijt} = \frac{GVA_{ijt}}{THW_{ijt}} e_{j2010}, \quad where\ i \in \mathrm{I}, \mathrm{j} \in \mathcal{J}\ and\ t \in \mathcal{T}\ , (1)$$

where GVA_{ijt} is real gross value added in millions of national currency in 2010 prices in industry i, country j and period t, THW_{ijt} is total hours worked (by employees or person engaged) in millions and e_{j2010} is the country-level nominal exchange rate expressed as US$/National Currency for the year 2010. Real Gross Value Added and Total Hours Worked were obtained through the EUKLEMS database. Nominal exchange rates for 2010 were obtained through the Organization for Economic Cooperation and Development (OECD) database.

Our main explanatory variable is robot density, which is obtained as the ratio of the operational stock of robots by millions of hours worked:

$$RD_{ijt} = \frac{R_{ijt}}{THW_{ijt}} \text{ , (2)}$$

where R_{ijt} is the physical operational stock of robots obtained through the International Federation of Robotics (IFR) database and THW_{ijt} is total hours worked in millions The dataset from the IFR has a few methodological challenges that had to be overcome, as already pointed out in Acemoglu & Restrepo (2018), Graetz & Michaels (2018), Artuc, E., Bastos, P., & Rijkers, B. (2020) and Jurkat et al. (2022), such as the absence of information on Operational Stock of Robots for several country-industry-time, where all apparently missing data are concentrated under an ´unspecified´ category, and the fact that this series is constructed in such a way that robots do not depreciate at all for 12 years, losing all their productive use at once after this period instead of smoothly over time.

To solve these problems, we follow Acemoglu & Restrepo (2018), Graetz & Michaels (2018) as well as Artuc, E., Bastos, P., & Rijkers, B. (2020) and first distribute the operational stock of robots under the ´unspecified´ category to all the industries in a country for a given year using as a distributive factor the time average fraction of each industry´s robot stock in the overall stock of robots when data becomes available for all industries in a country. The fraction of 'unspecified' robots that every industry receives is expressed as follows:

$$F_{ijt} = \frac{\sum_{t \,\epsilon\, \mathcal{T}} R_{ijt}}{\sum_{t \,\epsilon\, \mathcal{T}} \sum_{i \,\epsilon\, \mathrm{I}} R_{ijt}} \text{ (3)}$$

Given that, with the above method, we obtain data for all missing industries in the time range, we are at this point able to construct a new series for the Operational Stock of Robots, by means of a Perpetual Inventory Method (PIM), using the original data from robot stock as initial conditions and a flow series of robot sales (robot installations) also provided by the IFR.

$$R_{ijt} = I_{ijt} + (1-\delta)R_{ijt-1} \text{ , (4)}$$

where R_{ijt} is the end-of-period PIM operational stock of robots, I_{ijt} is the flow of robot installations, δ is the depreciation rate and R_{ijt-1} is the last year end-of-period operational robot stock. By doing this, we create a stock series where robots gradually depreciate, losing their productive use exponentially over time instead of abruptly. In creating the operational stock, we assume a standard 10% depreciation rate.

2.2.Empirical Model

We also follow the main approach of Graetz & Michaels (2018) and use as the main regressor of our model the percentile of the variation of robot density between the end and the beginning of the different sample periods, i.e. 1997-2007, 2008-2017 and 1997-2017. Therefore, our panel reduces to a cross-section of countr-industries in which we test the following linear regression model:

$$\Delta \ln LP_{ijt,t+h} = \beta_0 + \beta_1 \frac{\text{percentile of } \Delta \left(\frac{\#Robots_{ijt}}{Hours_{ijt}} \right)_{i,j,t,t+h}}{100} + \sum_{n=1}^{13} \rho_n X_n + \varepsilon_{ij} \quad (5)$$

The strategy of using the percentile of the variation in robot density is important to address the fact that the distribution of robot density growth is highly skewed to the right, making it difficult to fit a linear model between labor productivity and robot density growth (Graetz & Michaels, 2018). As for the variables: $\Delta \ln LP_{ijt,t+h}$ denotes the growth rate of labor productivity between periods $t \; and \; t+h$, X_n is a dummy variable or country fixed-effect that equals zero when $n \neq j$ and equals one when $n = j$; ε_{ij} is a country-industry *i.i.d.*. error term. The regression is weighted by 1997 industry share of hours worked (by employees or by person engaged, depending on the specification) with the purpose of attributing more importance to the most representative economic sectors in the initial period.

Our empirical strategy is motivated by the task-based models mentioned in the Introduction which imply that labor productivity is a direct function of robot density. But it is also true that robot density is a function of labor productivity, since higher labor productivity, and therefore higher wages, create an incentive to assign tasks previously performed by workers to robots (Zeira, 1998; Acemoglu & Restrepo, 2018; Graetz & Michaels, 2018). For that matter, it is important to address this source of endogeneity. GM find a strong and positive correlation between robot densification and the share of replaceable tasks within each industry, making it a good instrument for the intensity in which robots are used in industries due to its more structural, technologically oriented, and exogenous characteristics. Another motivation to use this instrumental variable is that in a task-based framework, automation is understood as an increase in the share of tasks performed by machines (Acemoglu & Restrepo, 2018). Several authors use this replaceability index as an instrument for robot density, among them Acemoglu & Restrepo (2022), where the central idea is to match information about occupations in the US Census with the IFR´s definition of core tasks performed by robots. The first step is to map the tasks robots perform (e.g. welding, painting, packing…) onto the 2000 US Census Occupational Classification at the three-digit level: if at least one of the many tasks performed by robots are in the description or the title of a given occupation, GM attribute a value of 1 to the occupation and 0 otherwise.[2] The main idea is that if one or more occupations in the 2000 Census map to one occupation in the 1990 Census, and at least one of the 2000´s occupations was assigned a value of one, the 1990 occupation is also assigned a value of one. Following the same steps, tracing occupations to the 1980 Census, they calculate the fraction of hours of 1980´s occupations that were susceptible to substitution in the future with respect to the total. The Replaceability Index is, therefore, the 1980´s share of replaceable hours by industry. We use the Replaceability index calculated by Acemoglu & Restrepo (2020), matching the industries for which they calculated the index with the ISIC Rev.4 classification used by both EUKLEMS and IFR.

Since we also want to understand the distributional effects of robotization on labor productivity, we will also estimate a conditional quantile location-scale model of the form:

$$Quant_{\theta}\left(\Delta \ln LP_{ijt,t+h} \middle| \boldsymbol{X}'_{ijt,t+h}\right) = \delta q(\theta) + \frac{\text{percentile of } \Delta\left(\frac{\#Robots_{ijt}}{Hours_{ijt}}\right)_{i,j,t,t+h}}{100}(\rho + \eta q(\theta)) + \sum_{n=1}^{13} X_n\left(\xi + \emptyset q(\theta)\right) \quad (6)$$

Through the Machado & Santos Silva (2019) Method of Moments Quantile Regression Estimator, we will assess the impact of variation in robot density growth on the whole distribution of labor productivity: $Quant_{\theta}\left(\Delta \ln LP_{ijt,t+h} \middle| \boldsymbol{X}'_{ijt,t+h}\right)$ represents the quantile of the variation in labor productivity conditional on a vector of regressors (in our case the vector reduces degenerates to a one-dimensional while $\delta q(\theta)$stands for the quantile fixed-effects for country-industry pairs and $(\rho + \eta q(\theta))$ is the quantile coefficient of robotization, i.e. the impact of robot density on the distribution of labor productivity. Again, X_n is a dummy variables or quantile country fixed-effect that equals zero when $n \neq j$ and equals one when $n = j$. This method is particularly useful to estimate a quantile regression in a setting in which the explanatory variable(s) are potentially endogenous, as is in our case.

[2] After several crosswalks among the 1980, 1990 and 2000 censuses, it is possible for them to map occupations through time and work recursively to identify occupations in 1990 and 1980 that had potential to be substituted by robots.

2.3.Summary statistics

In this section we organize the most important summary statistics of the variables of interest for the initial year (1997) for all 14 countries considered. From left to right, we have the logarithms of labor productivity, value-added, hours worked. For comparability purposes, we display below our own summary statistics for the beginning of the sample, alongside with the original 1997 summary statistics from the GM database. For each country, all of our summary statistics are weighted by 1997 share of hours worked by person engaged for each ISIC Rev. 4 industry. In the case of the GM summary statistics, variables are weighted by 1993 share of hours worked by person engaged, following their first sample year for weights. The robot density variation distribution is in the Appendix (Figure A.1).

Table 1. Summary statistics for the logs of Labor Productivity, Value-Added, Hours Worked and Robot Density by country for the beginning of the sample (1997)

Country	$\ln\left(\frac{VA}{H}\right)$		$\ln(VA)$		$\ln(H)$	
	This work	GM	This work	GM	This work	GM
Austria	3.36	3.10	9.01	8.32	5.64	5.22
Czech Republic	2.37	--	8.38	--	6.01	--
Germany	3.76	3.24	11.37	10.24	7.61	7.01
Denmark	3.92	3.36	8.87	7.86	4.95	4.50
Spain	3.45	3.20	10.47	9.94	7.01	6.75
Finland	3.55	3.12	8.69	7.90	5.14	4.78
France	3.63	3.35	10.83	10.22	7.20	6.87
Great Britain	3.32	3.26	10.08	10.17	6.76	6.91
Greece	2.61	2.56	8.86	8.59	6.25	6.03
Italy	3.44	3.11	10.80	9.97	7.35	6.86
Lithuania	1.02	--	5.06	--	4.03	--
Netherlands	3.85	3.48	9.78	9.02	5.92	5.53
Sweden	3.69	3.09	9.23	8.16	5.53	5.07
United States	3.60	3.32	12.19	11.89	8.59	8.57

Distributions are weighted by 1997 share of hours worked by ISIC Rev.4 industries for each country

Table 2. Summary statistics for the logs of Labor Productivity, Value-Added, Hours Worked and Robot Density by economic sector for the beginning of the sample (1997)

Country	$\ln\left(\frac{VA}{H}\right)$		$\ln(VA)$		$\ln(H)$	
	This work	GM	This work	GM	This work	GM
Agriculture	2.47	2.51	9.20	9.30	6.82	6.78
Mining	4.89	4.47	8.43	8.27	3.72	3.81
Food products	3.64	3.44	9.58	9.38	6.00	5.94
Textiles	3.01	2.91	8.35	8.31	5.37	5.39
Wood and Paper products	3.35	3.32	9.06	8.58	5.79	5.26
Chemicals & Other Mineral	4.00	3.77	10.03	9.21	6.04	5.44
Basic metals	3.58	3.37	9.59	9.28	6.06	5.90
Computer & Electronics	3.37	3.09	8.86	8.76	5.53	5.68
Machinery	3.50	--	9.00	--	5.56	--
Transport Equipment	3.58	3.37	8.89	8.68	5.34	5.31
Utilities	4.60	4.45	9.76	9.21	5.21	4.76
Construction	3.46	3.33	10.44	10.35	7.04	7.02
Education	3.65	3.47	10.27	10.23	6.63	6.76

For the sectors treated differently in GM, we aggregate the data by calculating a 1997 weighted average between the variables.

From Tables 1 and 2, we notice that the comparison between the descriptive statistics obtained by our own analysis and the one by GM show a high level of consistency on average. For example, at the beginning of the period, using the same Perpetual Inventory Method (PIM) with a 10% rate depreciation to calculate a new series for the stock of robots, both papers rank Germany, Sweden, Italy, France and Finland as the five most robotized countries in the sample. At the same time, both of our databases rank Transport Equipment, Basic Metals, Chemicals, Computer & Electronics and Food Products as the five most robotized sectors in the economy.

III. The first period: before the global financial crisis (1997-2007)

In this section, we will work with the first part of our sample (1997-2007) to observe how the results compare with those obtained by GM in the 10 years before the global financial crisis. We consider two different normalization assumptions when it comes to adjusting variables to per hour values: (i) hours worked by employees and (ii) hours worked by person engaged (also used by GM).[3] For this period, our results are close to those obtained by GM when using the same specifications. The variation in the logarithm of labor productivity moves on the range of 0.41-0.76 (normalization by hours worked by total employees) and 0.34-0.62 (normalization by hours worked by total persons engaged), whereas GM estimates an interval of 0.36-0.57, using the normalization (ii) by hours worked by total persons engaged.[4]

Table 3a. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked: First period (1997-2007): OLS and IV Estimates

	$\triangle$ ln (VA/H)		$\triangle$ ln (VA)		$\triangle$ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.406***	0.339***	0.245**	0.325***	-0.160**	-0.014
	(0.100)	(0.110)	(0.104)	(0.110)	(0.08)	(0.114)
B. Instrumental Variable						
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.684***	0.524***	0.272***	0.364***	-0.410***	-0.160
	(0.107)	(0.118)	(0.102)	(0.106)	(0.105)	(0.131)
First-stage F-statistic	226.0	231.4	226.0	231.4	226.0	231.4
Observations	185	173	185	173	185	173
Country Trend	No	No	No	No	No	No

Robust standard errors in parenthesis. Regressions weighted by each industry's 1997 share of hours within a country. Models 1,3 and 5 normalize variables by total hours worked by employees whereas models 2, 4 and 6 normalize variables by total hours worked by persons engaged.

[3] In the Appendix (Tables A1a and A1b) we provide the main results for the replication we did of GM´s paper, Robots at Work, using the same sample and database. As usual the variable *hours worked by employee* is less elastic to short-run shocks than the variable *hours worked by people engaged*. It is interesting to note the difference obtained for the coefficient of robotization in both variables, indicating that robotization tend to substitute more hours worked by more rigid employment than by more flexible employment.

4 Thus, our estimations of 0.34-0.62 compare with the GM's of 0.36-0.57. For a direct replication exercise see Tables A1a and A1b in the Appendix. Figure A2 in the Appendix also replicates Figures 2.A (left hand side) in GM.

In order to move from variations in log points to actual acceleration in labor productivity annual growth rates, we must use the calculated coefficients in the following way: $\left(e^{\frac{\beta}{n}}-1\right)x\ 100$, with *n* being the number of years in the time period. In terms of annual increases of labor productivity growth due to robotization, our numbers suggest an interval from 4.1 to 7.9 percentage points in the first case (i) and from 3.4 to 5.2 percentage points in the second (ii). In the same setting (ii), GM´s numbers translate into an acceleration on the range of 2.6-4.1 percentage points. It is worth noting that the most robust results are those from country fixed-effects IV regressions which points for values of 6.3 and 7.9 percentage points. Thus, we obtain a slightly higher effect of robotization that can only be due to the differences coming by data, already described, namely that in this exercise we are using less 4 years (1993-1996) than GM's and more 3 countries.

In Table 3a., it is interesting to note that the effect of robotization on value-added growth is the main source of the increase in labor productivity, even in the case where the growth of hours worked responds negatively and significantly to robotization (column 5). When we estimate a model with country fixed-effects (Table 3b), we also see the same pattern is obtained.

Table 3b. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked: First period (1997-2007): OLS and IV Estimates

	$\triangle$ ln (VA/H)		$\triangle$ ln (VA)		$\triangle$ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\triangle$ $(\#\frac{robots}{hours})/100$	0.549***	0.505***	0.390***	0.434***	-0.158**	-0.071
	(0.099)	(0.106)	(0.093)	(0.098)	(0.072)	(0.082)
B. Instrumental Variable						
Percentile of $\triangle$ $(\#\frac{robots}{hours})/100$	0.763***	0.624***	0.369***	0.412***	-0.394***	-0.212**
	(0.098)	(0.105)	(0.090)	(0.093)	(0.099)	(0.104)
First-stage F-statistic	231.3	239.9	231.3	239.9	231.3	239.9
Observations	185	173	185	173	185	173
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis. Regressions weighted by each industry's 1997 share of hours within a country. Models 1,3 and 5 normalize variables by total hours worked by employees whereas models 2, 4 and 6 normalize variables by total hours worked by persons engaged.

In this period, labor productivity growth is being pushed upwards by a fast increase in value-added, highlighting the beneficial effects of robots on raising production: in the more robust scenarios, using the Replaceability Index as an instrumental variable and country fixed-effects, the proportion of labor productivity growth that came from value-added growth is around 2/3 when using the GM hours worked variable – normalization (ii), while the other 1/3 came from a reduction in hours worked.

IV. New results for the recent period and comparison: 1997-2017 and 2008-2017

In Tables 4a. and 4b., we show the results for whole sample, between 1997 and 2017, and observe that when compared with results in Tables 3a and 3b, the effect of robotization on labor productivity growth is more pronounced than in the 1993-2007 period. We find that robots increase labor productivity growth in the interval 3.5 – 4.6 percentage points and 2.5 – 3.1 percentage points depending on the type of normalization. When compared to the previous results, focused on the first period, it is worth noting that the annual labor productivity growth led by robots density is almost halved. This non-neglible decrease in the annual effect of robotization in labor productivity is one of the main results we want to highlight and develop.

The upward movement in labor productivity growth is often driven more by the positive effects of robotization on value-added growth than on the decrease in hours worked. When we adjusted variables by hours worked by employees (even columns in the tables), we observe again that the importance of a reduction in the growth rate of hours worked to the growth in labor productivity increases. It is also worth noting that in the IV estimations the quantitative relevance of hours worked in the explanation of the productivity is now increased and in some cases, it even overcome the quantitative effect on added value. The pattern is maintained with country fixed-effects (Table 4b).

Table 4a. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked: Full sample (1997-2017): OLS and IV Estimates

	$\triangle \ln (VA/H)$		$\triangle \ln (VA)$		$\triangle \ln (H)$	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\triangle (\# \frac{robots}{hours})/100$	0.682***	0.497***	0.431***	0.436***	-0.251**	-0.061
	(0.150)	(0.180)	(0.141)	(0.146)	(0.104)	(0.109)
B. Instrumental Variable						
Percentile of $\triangle (\# \frac{robots}{hours})/100$	0.903***	0.611***	0.347***	0.356***	-0.556***	-0.255*
	(0.131)	(0.178)	(0.116)	(0.128)	(0.125)	(0.144)
First-stage F-statistic	266.5	241.6	266.5	241.6	266.5	241.6
Observations	128	116	128	116	128	116
Country Trend	No	No	No	No	No	No

Robust standard errors in parenthesis. Regressions weighted by each industry's 1997 share of hours within a country. Models 1,3 and 5 normalize variables by total hours worked by employees whereas models 2, 4 and 6 normalize variables by total hours worked by persons engaged.

Table 4b. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked: Full sample (1997-2017): OLS and IV Estimates

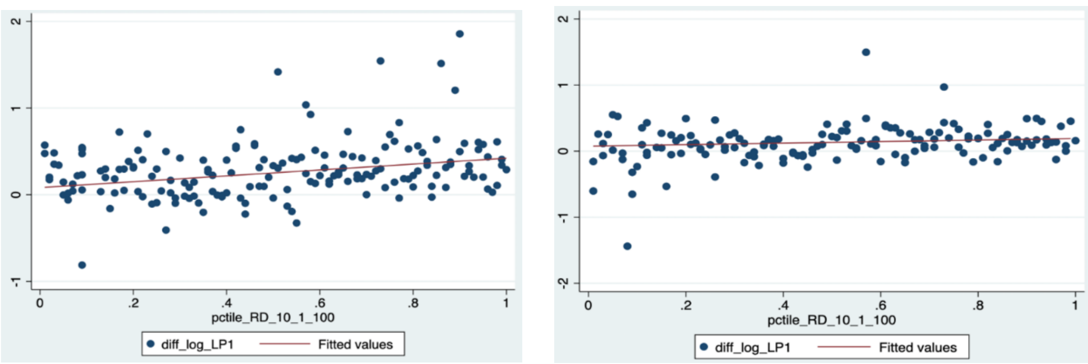
	$\triangle \ln (VA/H)$		$\triangle \ln (VA)$		$\triangle \ln (H)$	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\triangle\ (\#\frac{robots}{hours})/100$	0.781***	0.563***	0.502***	0.501***	-0.278***	-0.062
	(0.153)	(0.182)	(0.151)	(0.152)	(0.104)	(0.112)
B. Instrumental Variable						
Percentile of $\triangle\ (\#\frac{robots}{hours})/100$	0.878***	0.588***	0.335***	0.336***	-0.542***	-0.252*
	(0.117)	(0.157)	(0.113)	(0.117)	(0.118)	(0.135)
First-stage F-statistic	310.4	282.1	310.4	282.1	310.4	282.1
Observations	128	116	128	116	128	116
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis. Regressions weighted by each industry's 1997 share of hours within a country. Models 1,3 and 5 normalize variables by total hours worked by employees whereas models 2, 4 and 6 normalize variables by total hours worked by persons engaged.

In fact, we want to explore this apparent slowdown in the effect of robotization when considering a much lengthier period.[5] We wonder that this result comes from a much lower effect of robotization in the period coinciding to the financial crisis and the post-crisis period. This is the reason why we pin down the timeframe between two main periods, adding now results for the 2008-2017 period.

Below, we contrast the scatter plots and the linear fit of labor productivity growth and the percentile of robot density growth in the two subsamples, namely 1997-2007 and 2008-2017. It is clear from the Figure 1 that the slope of the curve in the first sample is higher than in the second, where it appears to be almost horizontal. This first exploratory analysis suggests that labor productivity growth before the financial crisis correlates more with an acceleration of robot density.[6]

Figure1. Changes in Robots Input and Growth rate of Productivity (1997-2007 on the left and 2008-2017 on the right): weighted OLS



[5] It is worth noting that when comparing two periods 1993-2000 and 2000-2007, GM found a lower IV estimates for their second period.
[6] As expected the first figure at the left is quite close to the Figure 2.A at Graetz and Michaels (2018).

Between 2008 and 2017, the effect of robotization on labor productivity, although still positive and statistically significant, the variation in log points falls by as much as 45% when we compare column 1 of tables 3a. and 5a. and by as much as 66% when we compare columns 2 of both tables. We estimate that robotization increases the growth rate of labor productivity in this period in the range of 2.3-3.6 and 1.6-2.3 percentage points, much below the pattern observed in the initial sample, and below the pattern in the whole period. It is worth noting again that the most robust results in country fixed-effects IV regressions points for values of 2.3 or 3.6 percentage points. Thus, the result obtained for the whole sample roots undoubtfully in the very smaller effect of robotization in annual productivity growth in the most recent 10-year period.

This result is in line with the secular stagnation argument literature that analyzes why advanced economies are trapped in a low productivity long-run equilibrium. One possible explanation for this phenomenon, following Gordon (2015) and Sequeira et. al. (2018), is that there are diminishing returns to innovation, which means that new technologies such as robotics and artificial intelligence may not increase productivity growth as much as the Industrial Revolution's technologies, such as the massification of electricity and the use of steam engine did back in the 19^{th} and early 20^{th} century.

Table 5a. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (2008-2017): OLS and IV Estimates

	$\triangle \ln (VA/H)$		$\triangle \ln (VA)$		$\triangle \ln (H)$	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.224***	0.116	0.141**	0.151**	-0.083*	0.034
	(0.060)	(0.077)	(0.066)	(0.073)	(0.047)	(0.044)
B. Instrumental Variable						
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.331***	0.205**	0.109	0.118	-0.222***	-0.087
	(0.079)	(0.095)	(0.080)	(0.086)	(0.071)	(0.069)
First-stage F-statistic	197.9	194.8	197.9	194.8	197.9	194.8
Observations	146	134	146	134	146	134
Country Trend	No	No	No	No	No	No

Robust standard errors in parenthesis. Regressions weighted by each industry's 1997 share of hours within a country. Models 1,3 and 5 normalize variables by total hours worked by employees whereas models 2, 4 and 6 normalize variables by total hours worked by persons engaged.

It is also interesting that, in some cases, as in part B of Table 5b, the reduction in the growth rate of hours worked induced by robotization, independently of the type of the hours used to normalize the variables, is much more important for the growth of labor productivity than the growth rate of value-added. If we compare the results of part B of Tables 3b. and 5b. with country-fixed effects, we even observe that the effect of robotization on value-added growth turns out to be no longer statistically significant. In summary, the effect of robots on value-added growth falls by as much as 78% between the two subsamples while the effect of robots on hours worked growth increases by 33% in the same comparison. Another way to see this change is by observing that value-added growth accounted 66% percent of labor productivity growth in the first part of the sample while only 41% in the second part, showing a lower ability of robots to increase productivity growth by accelerating value-added growth. Instead, most of the poorer increase in labor productivity growth from 2008 onwards comes from a reduction in hours worked.

As we pointed out in the introduction, this result may uncover a shifting bias from value-added creation of robotic technology to a more labor-hours substitution bias, which, if revealed to be true, marks a problematic aspect of robotic technology, which is to substitute labor without being significantly more productive than the labor it substitutes. This result constrains the capacity for the creation of new tasks in the economy and blocks the demand and reinsertion of unemployed labor in new and more labor-intensive tasks (Acemoglu & Restrepo, 2019).

Table 5b. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (2008-2017): OLS and IV Estimates

	$\triangle$ ln (VA/H)		$\triangle$ ln (VA)		$\triangle$ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\triangle\ (\#\frac{robots}{hours})/100$	0.263***	0.156**	0.145**	0.153**	-0.118***	-0.002
	(0.061)	(0.079)	(0.073)	(0.082)	(0.046)	(0.045)
B. Instrumental Variable						
Percentile of $\triangle\ (\#\frac{robots}{hours})/100$	0.351***	0.229***	0.096	0.094	-0.255***	-0.136**
	(0.069)	(0.088)	(0.074)	(0.083)	(0.063)	(0.063)
First-stage F-statistic	216.2	197.6	216.2	197.6	216.2	197.6
Observations	146	134	146	134	146	134
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis. Regressions weighted by each industry's 1997 share of hours within a country. Models 1,3 and 5 normalize variables by total hours worked by employees whereas models 2, 4 and 6 normalize variables by total hours worked by persons engaged.

In an essay and a series of theoretical and empirical analysis, Acemoglu warns about the possible effects of what he calls 'so-so' robotic technological improvements (Acemoglu, 2020), which mainly substitutes labor in the production process without significantly increasing labor productivity. This kind of technological improvement stalls the demand for labor, as machines are productive enough to create new tasks and job opportunities in the economy.

V. Quantile Regressions approach

In the theoretical literature, Acemoglu & Restrepo (2020) develop a task-based model with heterogenous labor (low and high skill) where one of the implications is the possibility for different effects of robotization, equivalent to an increase in the share of total tasks performed by machines, on the labor productivity of each of these groups. Quantile regression is a powerful empirical tool to investigate these kinds of asymmetric effects on the dependent variable. Below we present six tables that estimate quantile coefficients with country fixed-effects for all the two subsamples, i.e. 1997-2007 and 2008-2017 and for the whole sample (1997-2017).

Table 6. Changes in Robots Input and Growth on Productivity: First period (1997-2007): Quantile Regression and IV Quantile Regression

	Quantile coefficients								
	$\theta = .1$	$\theta = .2$	$\theta = .3$	$\theta = .4$	$\theta = .5$	$\theta = .6$	$\theta = .7$	$\theta = .8$	$\theta = .9$
	A. Quantile Regression								
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.391***	0.295***	0.294***	0.335***	0.259***	0.311***	0.323***	0.321***	0.240**
	(0.106)	(0.083)	(0.103)	(0.085)	(0.101)	(0.091)	(0.103)	(0.096)	(0.110)
	B. IV Quantile Regression								
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.583***	0.565***	0.546***	0.533***	0.521***	0.509***	0.501***	0.488***	0.459*
	(0.154)	(0.122)	(0.104)	(0.105)	(0.118)	(0.136)	(0.151)	(0.179)	(0.249)
Observations	173	173	173	173	173	173	173	173	173
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis.

We can observe that in the first ten years of the sample, all quantile coefficients are positive and statistically significant at least at the 10% significance level. The main pattern we observe when we estimate the model without any instrument is that the effects of robotization on labor productivity growth tendentially decrease until the 5th decile and starts to increase again until the 7th decile. Even with this rebound of the effect for the right half of the distribution, the overall pattern is one of decreasing magnitude as we go along the productivity growth distribution. This pattern becomes clearer when we introduce the Replaceability Index as an instrument for robotization, where we see a monotonic decrease in the effect of robotization on labor productivity growth. It is now worth noting that for the most robust results in country fixed-effects IV regressions points out that robotization increases productivity growth in nearly 6 percentage points for the least productive sectors and in nearly 4.7 percentage points for the most productive sectors.

Table 7.Changes in Robots Input and Growth on Productivity: First period (2008-2017): Quantile Regression and IV Quantile Regression

	Quantile coefficients								
	$\theta = .1$	$\theta = .2$	$\theta = .3$	$\theta = .4$	$\theta = .5$	$\theta = .6$	$\theta = .7$	$\theta = .8$	$\theta = .9$
	A. Quantile Regression								
Percentile of $\triangle (\# \frac{robots}{hours})/$ 100	0.311	0.245**	0.154**	0.171**	0.159**	0.159**	0.192***	0.169*	0.037
	(0.207)	(0.113)	(0.071)	(0.076)	(0.074)	(0.068)	(0.069)	(0.094)	(0.112)
	B. IV Quantile Regression								
Percentile of $\triangle (\# \frac{robots}{hours})/$ 100	0.385***	0.354***	0.336***	0.316***	0.302***	0.291***	0.274***	0.256**	0.218
	(0.111)	(0.090)	(0.084)	(0.085)	(0.090)	(0.096)	(0.109)	(0.125)	(0.165)
Observations	147	147	147	147	147	147	147	147	147
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis.

The same overall pattern can be observed in the last ten years of the sample (2008-2017), where the coefficients decline almost monotonically throughout the quantiles. Apart from this common aspect, we can identify at least two important differences: (i) all quantile coefficients are around half as lower in the second period, confirming the reduction in the average effect of robotization on labor productivity growth from last section analysis. Even though all quantile coefficients fall from the first to the second subsamples, the decrease intensifies as we go along the quantiles; (ii) the coefficients of higher quantiles of the labor productivity growth distribution lose statistical significance. In these second-period regressions, robotization increases productivity growth in nearly 3.9 percentage points for the least productive sectors and in nearly 2.2 percentage points for the most productive sectors, almost halving the effects of the first period.

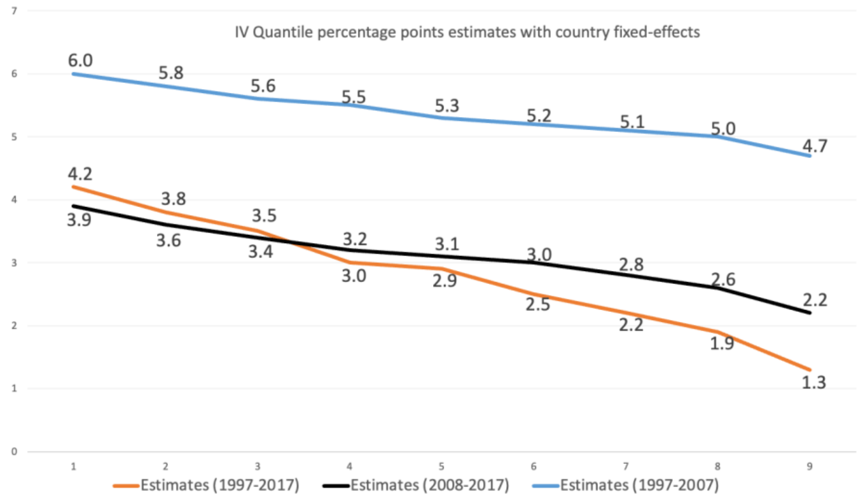
Table 8.Changes in Robots Input and Growth on Productivity: Full sample (1997-2017): Quantile Regression and IV Quantile Regression

	Quantile coefficients								
	$\theta = .1$	$\theta = .2$	$\theta = .3$	$\theta = .4$	$\theta = .5$	$\theta = .6$	$\theta = .7$	$\theta = .8$	$\theta = .9$
	A. Quantile Regression								
Percentile of $\triangle (\# \frac{robots}{hours})/$ 100	0.649***	0.652**	0.375**	0.321*	0.350**	0.241*	0.332**	0.368*	0.371*
	(0.198)	(0.267)	(0.154)	(0.169)	(0.159)	(0.122)	(0.153)	(0.184)	(0.196)
	A. IV Quantile Regression								
Percentile of $\triangle (\# \frac{robots}{hours})/$ 100	0.826***	0.747***	0.696***	0.597***	0.543***	0.488***	0.432**	0.369*	0.259
	(0.157)	(0.137)	(0.133)	(0.140)	(0.152)	(0.169)	(0.191)	(0.219)	(0.274)
Observations	116	116	116	116	116	116	116	116	116
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis.

When we conduct the same exercise for the whole sample (1997-2017), we observe the same pattern of tendentially decreasing quantile coefficients and loss of statistical significance as we go along the labor productivity growth distribution. And just as the average model showed, the effects of robotization are significantly higher for the whole sample than for the initial period that approximates the database of Graetz & Michaels (2018). We plot below the quantile percentage points increase in labor productivity for each relevant decile of the labor productivity distribution for all the subsamples using the Replaceability Index as our instrumental variable along with quantile country fixed-effects (we provide in the Appendix percentage points quantile estimates with 95% confidence intervals).

Figure2. Changes in Robots Input and annual percentage points increase of Productivity by labor productivity deciles



The coefficients' values in the total sample reflects the effect we observed in the second 2008-2017 period, in which the effect of robotization decreases a lot, even more for the highest deciles. This may indicate that the most productive sectors, relying on skilled and complex tasks are now robotizing those tasks with small or null effect in productivity growth. For the period taken as a whole, robotization increases productivity growth in nearly 4.2 percentage points for the least productive sectors and in nearly 1.3 percentage points for the most productive sectors. Also note that for the last decile both in the second period (2008-2017) and the whole period (1997-2017) the coefficient of the last decile is not statistically different from zero at the usual significance levels (10% or less).

VI. Conclusion

In this paper we analyze how automation, specifically robotic automation, has impacted labor productivity growth in a period of 20 years, between 1997-2017, and how this relationship changed between the first ten years and the last ten years of the sample marked by the global financial crisis.

In the first part, we approximate Graetz & Michaels (2018), a paper that studies the effects of robotization on labor productivity growth between 1993 and 2007, in order to obtain approximate but comparable summary statistics and estimated coefficients. We find that the effects of robotization on labor productivity growth are statistically significant and range between 3.4-7.9 percentage points.

In the second part, from 2008 to 2017 we observe an important deceleration in the labor productivity growth induced by robotization. We estimate the effect now ranges between 1.5-3.6 percentage points, which higher bound is rather close to the lower bound of the 1997-2007 period.

Another important result is the change in the composition of the sources of productivity growth. In the second half of the sample, the importance of robotization induced value added increase to labor productivity growth falls significantly when compared to first part of the sample, while the effect of robotization on declining hours worked becomes more important to the dynamics of labor productivity growth. In the period 1997-2007, value-added growth induced by robots accounted for almost 2/3 of labor productivity increase while this number dropped to just 41% in the post-crisis period, suggesting that not only the pace of labor productivity growth decreased but that it has been mainly driven by the fall of hours worked.

We also conducted a quantile regression analysis with the same samples and found that this method corroborated the decreasing effect of robotization on labor productivity growth from the period 1997-2007 to the period 2008-2017. The effect of robotization on labor productivity growth was found to be decreasing in the quantiles for all the samples analyzed, meaning that less productive sectors benefited more from robotization across all periods. Besides that, we also found that, between the first and second samples, the robotization effect fell for all the 9 deciles analyzed, suggesting that robots lost, since the 2008 crisis, their ability to foster labor productivity growth on every relevant part of the conditional labor productivity distribution. From the regressions, we also discovered that this falling effect was more prominent in the higher quantiles, meaning that the high productivity sector are indeed the ones in which the robotization effect in productivity growth has fallen the most.

This result can also be one of the possible reasons for the so-called secular stagnation, in the lines of Gordon (2015) and Sequeira et al. (2018), a situation of prolonged low productivity growth that may be related to supply-side conditions, such as the capability of new technologies, such as robotics and artificial intelligence, to deliver sustained economic growth, which also roots on the argument from Acemoglu and Restrepo, (2019) about the 'so-so' robotic technological improvements which mainly substitutes labor in the production process without significantly increasing labor productivity.

References

Acemoglu, D., & Restrepo, P. (2018). Modeling Automation. *AEA Papers and Proceedings, 108*, 48–53. https://doi.org/10.1257/pandp.20181020

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2), 3-30. http://dx.doi.org/10.1257/jep.33.2.3

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy 128(6)*, 2188-2244. http://dx.doi.org/10.1086/705716

Acemoglu, D., & Restrepo, P. (2022). Demographics and automation. The Review of Economic Studies, 89(1), 1-44. https://doi.org/10.1093/restud/rdab031

Autor, D., C. Goldin, and L.F. Katz (2020). Extending the race between education and technology. *AEA Papers and Proceedings 100*, 347-51. http://dx.doi.org/10.1257/pandp.20201061

Artuc, E., Bastos, P., & Rijkers, B. (2020). Robots, tasks, and trade (REM Working Paper No. 0118-2020). *Research in Economics and Mathematics*. https://rem.rc.iseg.ulisboa.pt/wps/pdf/REM_WP_0118_2020.pdf

Battisti, M., M. Del Gatto, and C.F. Parmeter (2021). Skill biased technical change and economic (in)efficiency: a country-sector perspective. *University of Miami Business School Research Paper No. 3397661*.

Graetz, G., & Michaels, G. (2018). Robots at work. In *Review of Economics and Statistics 100*(5), 753–768. https://doi.org/10.1162/rest_a_00754

Gordon, R. J. (2015). Secular stagnation: A supply-side view. *American economic review*, 105(5), 54-59. http://dx.doi.org/10.1257/aer.p20151102

Jurkat, A., Klump, R., & Schneider, F. (2022). Tracking the Rise of Robots: The IFR Database. Jahrbücher für Nationalökonomie und Statistik.

Machado, J. A. F., & Santos Silva, J. M. C. (2019). Quantiles via moments. *Journal of Econometrics*, *213*(1), 145–173. https://doi.org/10.1016/j.jeconom.2019.04.009

Sequeira, T. & Gil, P & Afonso, O. (2018). Endogenous growth and entropy. *Journal of Economic Behavior & Organization 154*, 100-120 https://doi.org/10.1016/j.jebo.2018.07.019

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics 70*(1), 65-94 . http://dx.doi.org/10.2307/1884513

Stehrer, R. (2021), wiiw Growth and Productivity Data. https://euklems.eu/

Timmer, M. & T. Van Moergastel & E. Stuivenwold & G. Ypma & M. O'Mahony, & M. Kangasniemi (2007): "EU KLEMS Growth and Productivity Accounts Version 1.0," mimeo, University of Groningen.

Zeira, J. (1998). Workers, machines, and economic growth. *The Quarterly Journal of Economics*, *113*(4), 1091-1117. http://dx.doi.org/10.1162/003355398555847

Appendix

Figure A1. Distribution of the variation in robot density between 1997 and 2017

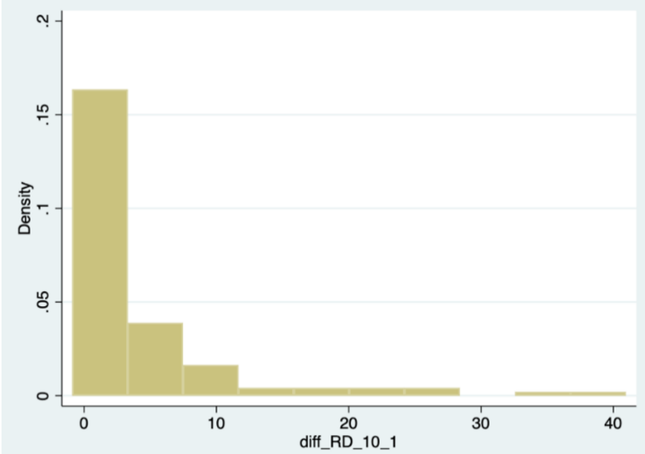


Figure A2. Changes in Robots Input and Growth on Productivity (1997-2017): weighted OLS

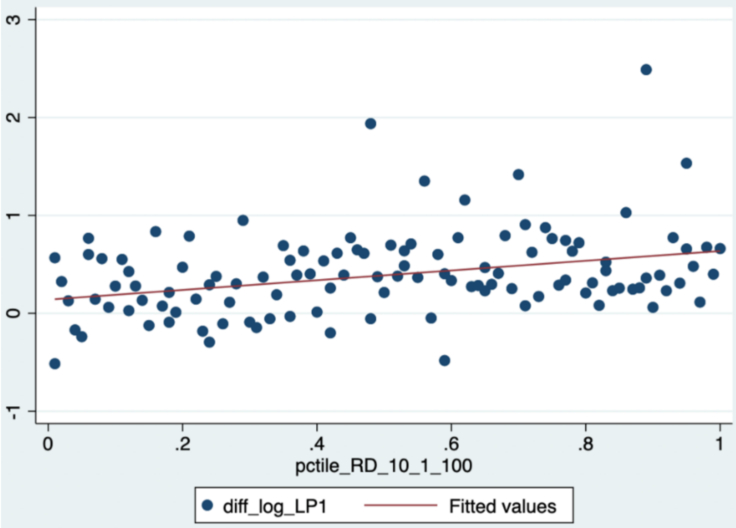


Table A1a. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (1993-2007): OLS and IV Estimates – without country trend

	$\triangle \ln(VA/H)$		$\triangle \ln(VA)$		$\triangle \ln(H)$	
	Current work	GM	Current work	GM	Current work	GM
A. OLS						
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.328***	0.359***	0.387***	0.336***	0.059	-0.023
	(0.125)	(0.106)	(0.136)	(0.117)	(0.116)	(0.114)
B. Instrumental Variable						
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.886***	0.833***	0.625***	0.545***	-0.261	-0.289
	(0.202)	(0.188)	(0.160)	(0.155)	(0.178)	(0.169)
First-stage F-statistic	122.1	93.7	122.1	93.7	122.1	93.7
Observations	238	238	238	238	238	238
Country Trend	No	No	No	No	No	No

Robust standard errors in parenthesis. Regressions weighted by each industry's 1993 share of hours within a country.

Table A1b. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (1993-2007): OLS and IV Estimates – with country trend

	$\triangle$ ln (VA/H)		$\triangle$ ln (VA)		$\triangle$ ln (H)	
	Current work	GM	Current work	GM	Current work	GM
A. OLS						
Percentile of $\triangle$ $(\#\frac{robots}{hours})/100$	0.569***	0.572***	0.652***	0.602***	0.08	0.03
	(0.131)	(0.118)	(0.139)	(0.121)	(0.104)	(0.099)
B. Instrumental Variable						
Percentile of $\triangle$ $(\#\frac{robots}{hours})/100$	0.925***	0.873***	0.693***	0.607***	-0.232	-0.266
	(0.166)	(0.157)	(0.146)	(0.143)	(0.162)	(0.155)
First-stage F-statistic	159.0	152.6	159.0	152.6	159.0	152.6
Observations	238	238	238	238	238	238
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis. Regressions weighted by each industry's 1993 share of hours within a country.

Table A2. Changes in Robots Input and Growth on Productivity: Full sample (1997-2017): Quantile Regression and IV Quantile Regression

	Quantile coefficients								
	$\theta = .1$	$\theta = .2$	$\theta = .3$	$\theta = .4$	$\theta = .5$	$\theta = .6$	$\theta = .7$	$\theta = .8$	$\theta = .9$
A. Quantile Regression									
Percentile of $\triangle$ $(\#\frac{robots}{hours})/100$	0.479***	0.501***	0.357**	0.283*	0.262*	0.426**	0.284*	0.269	0.469**
	(0.150)	(0.146)	(0.141)	(0.160)	(0.141)	(0.181)	(0.169)	(0.193)	(0.228)
B. IV Quantile Regression									
Percentile of $\triangle$ $(\#\frac{robots}{hours})/100$	0.667***	0.665***	0.663***	0.658**	0.655***	0.652***	0.648**	0.644**	0.638
	(0.144)	(0.128)	(0.123)	(0.148)	(0.177)	(0.217)	(0.266)	(0.317)	(0.418)
Observations	116	116	116	116	116	116	116	116	116
Country Trend	No	No	No	No	No	No	No	No	No

Robust standard errors in parenthesis.

Table A3. Changes in Robots Input and Growth on Productivity: First period (1997-2007): Quantile Regression and IV Quantile Regression

	Quantile coefficients								
	$\theta = .1$	$\theta = .2$	$\theta = .3$	$\theta = .4$	$\theta = .5$	$\theta = .6$	$\theta = .7$	$\theta = .8$	$\theta = .9$
A. Quantile Regression									
Percentile of $\triangle$ $(\#\frac{robots}{hours})/100$	0.267***	0.310***	0.257***	0.220***	0.164*	0.185**	0.250***	0.267**	0.178*
	(0.104)	(0.075)	(0.088)	(0.081)	(0.092)	(0.090)	(0.099)	(0.117)	(0.108)
B. IV Quantile Regression									
Percentile of $\triangle$ $(\#\frac{robots}{hours})/100$	0.424***	0.472***	0.498***	0.531***	0.575***	0.613***	0.660***	0.728***	0.848**
	(0.118)	(0.102)	(0.101)	(0.110)	(0.133)	(0.160)	(0.198)	(0.259)	(0.371)
Observations	173	173	173	173	173	173	173	173	173
Country Trend	No	No	No	No	No	No	No	No	No

Robust standard errors in parenthesis

Table A4. Changes in Robots Input and Growth on Productivity: First period (2008-2017): Quantile Regression and IV Quantile Regression

	Quantile coefficients								
	$\theta = .1$	$\theta = .2$	$\theta = .3$	$\theta = .4$	$\theta = .5$	$\theta = .6$	$\theta = .7$	$\theta = .8$	$\theta = .9$
	A. Quantile Regression								
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.397**	0.254***	0.193***	0.194***	0.161**	0.133	0.138	0.164	0.115
	(0.169)	(0.077)	(0.067)	(0.071)	(0.065)	(0.086)	(0.100)	(0.121)	(0.103)
	B. IV Quantile Regression								
Percentile of $\triangle\,(\#\frac{robots}{hours})/100$	0.378***	0.356***	0.349***	0.334***	0.321***	0.313***	0.298**	0.280*	0.265
	(0.124)	(0.103)	(0.098)	(0.099)	(0.106)	(0.114)	(0.132)	(0.159)	(0.185)
Observations	147	147	147	147	147	147	147	147	147
Country Trend	No	No	No	No	No	No	No	No	No

Robust standard errors in parenthesis.

Figure A.3. Changes in Robots Input and annual percentage points increase of Productivity by selected labor productivity deciles (1997-2017) - Dotted curves represent 95% confidence intervals

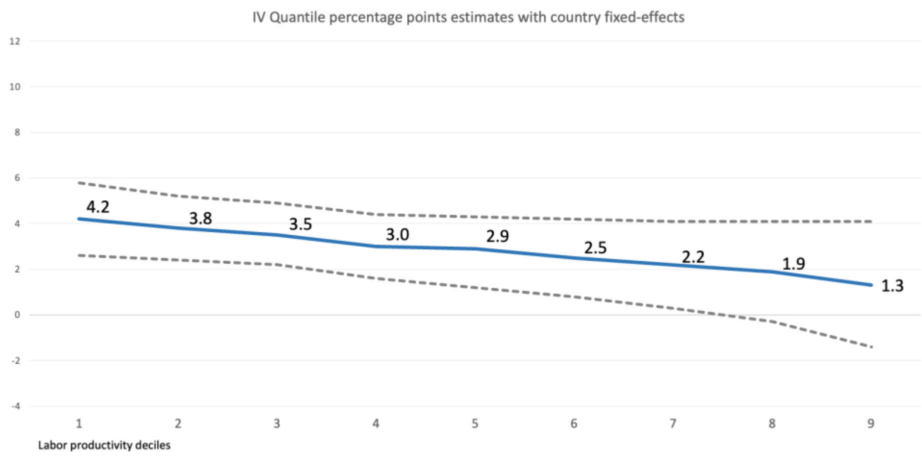


Figure A.4. Changes in Robots Input and annual percentage points increase of Productivity by selected labor productivity deciles (1997-2007) – Dotted curves represent 95% confidence intervals

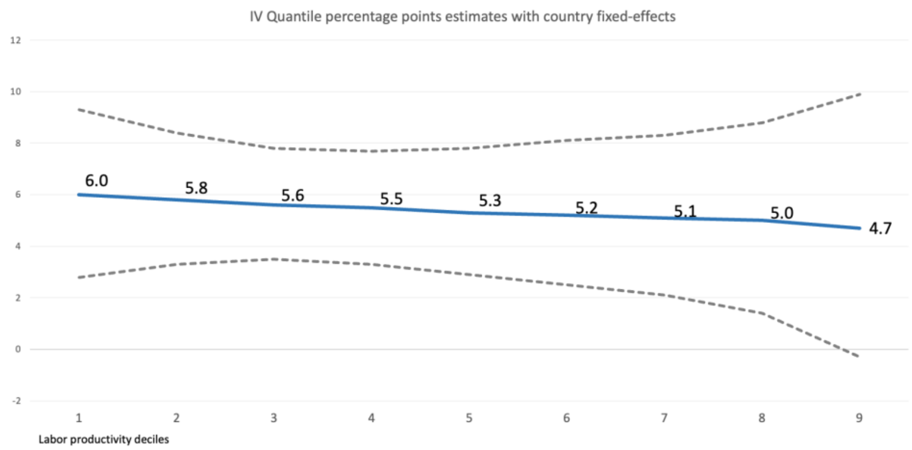


Figure A.5. Changes in Robots Input and annual percentage points increase of Productivity by selected labor productivity deciles (2008-2017) - Dotted curves represent 95% confidence intervals