Robots at work: new evidence with recent data§

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Abstract

We reassess the relationship between robotization and the growth in labor productivity in the light of more recent data. We discover that the effect of robot density in the growth productivity substantially decreased in the post-2008 crisis period. In this more recent period, the less strong positive effect of robot density in the growth of productivity depends less on the increase in the value added due to robotization. The data analysis dismisses any positive effect of robotization on hours worked. Results are confirmed by several robustness checks, cross-sectional IV and quantile regression analysis and through panel data quantile and IV analysis. By means of the quantile regression analysis, we 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 felt significantly throughout the distribution. 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

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I. Introduction

Robotization is among the cutting-edge General Purpose Technology (GPT) alongside with Artificial Intelligence (e.g. Acemoglu, 2018). Thus, the study of its effect on productivity is paramount. 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.

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 & 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.[1]

Even though the numbers are showing increased investment in automation and technological innovations, 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). Also Acemoglu warns about the possible effects of what he calls 'so-so' robotic technological

[1] 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.

improvements (Acemoglu et. al., 2020), which mainly substitutes labor in the production process without significantly increasing labor productivity.

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.

We extend Graetz & Michaels (2018) empirical analysis of the effects of robotization on labor productivity in three main dimensions. First, we extend the period of the analysis from 1993-2007 to 1997-2017. Second, we have included 10 more countries into the analysis. Third, we extend the analysis to use quantile regressions both in cross section and panel data. In fact, using a wider panel data, both in the year and in the country dimensions, we tend to corroborate Graetz & Michaels (2018) results for a comparable period but uncover new results when considering the newer period with the larger set of countries.

We discover that the effects of higher robot intensity over labor productivity falls greatly in the last 10 years, from 5.6-8.4 percentage points to 1.3-2.8 percentage points in the baseline scenario where we normalize hourly worked variables by total hours worked by person engaged. In both cases, the lower bound is given by the estimates of the OLS model with country fixed-effects 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 employee, the effects fall from 5.7-10.1 percentage points between 1997-2007 to 2.7-4.8

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. The quantile analysis while confirming a decrease in the effects of robots on the productivity variation from the first period to the second, it also highlights a new result according to which robots have higher positive elasticities for the first deciles of the labor productivity, i.e. indicating a type of decreasing returns to scale effect of robotization.

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),[2] for the period 1997-2007. In Section IV, we expand the 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 we describe the results of several robustness analysis. In Section VI, 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, extending the framework to consider panel data analysis. Finally, in Section VI we write the concluding remarks.

II. Methodology and data description

For this paper, we consider 25 countries for which we have available data (Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, Germany, Great Britain, Greece, Hungary, Ireland, Italy, France, Poland, Portugal, Lithuania, Netherlands,

[2] Referred as GM from here onwards.

Romania, Spain, Slovakia, Slovenia, Sweden and 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, although some observations for particular pairs of country-industry only appear after 1997 and, for the case of three countries (USA, Estonia and Ireland), the EUKLEMS delivers only partial information on the Chemicals sector.

Even though we work with the same database sources, our sample 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. Another 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, van Moergastel, Stuivenwold, Ypma, O'Mahony and Kangasniemi, 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 25 countries that we consider in the original sample, 15 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,[3] but with no fundamental difference as it will be clear in the comparison of our descriptive statistics and other results. In 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

[3] 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.

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).

Bellow, we provide an initial list 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 *by 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:

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

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) and 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:

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

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

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

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 country-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).[4] As for the variables: $\Delta \ln LP_{ijt,t+h}$ denotes the growth rate of labor productivity between periods $t \text{ and } t+h$, 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* and *by person engaged*, depending on the specification) with the purpose of attributing more importance to the most representative economic sectors in the initial period.

[4] Figure A1 (Appendix A1) plots the distribution, highlighting the skewness.

Our empirical strategy is motivated by the task-based models 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.[5] 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 &

[5] 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.

Restrepo (2020), matching the industries for which they calculated the index with the ISIC Rev.4 classification used by both EUKLEMS and IFR.

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 the 25 countries considered. From left to right, we have the logarithms of labor productivity, value-added, hours worked *by persons employed*. For comparability purposes, we display below our own summary statistics for the beginning of the sample, alongside with the 1997 weighted summary statistics from the GM database. For each country, our summary statistics are weighted by 1997 share of hours worked by person engaged for each ISIC Rev. 4 industry. The robot density variation distribution 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	5.65	5.22
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	3.54	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	3.52	3.26	10.80	10.17	7.29	6.91
Greece	2.61	2.56	8.86	8.59	6.25	6.03
Italy	3.44	3.11	10.79	9.97	7.35	6.86
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	3.64	3.32	12.25	11.89	8.61	8.57
Czech Republic	2.37	--	8.38	--	6.01	--
Slovenia	2.28	--	6.82	--	4.54	--
Slovakia	2.02	--	7.23	--	5.21	--
Ireland	2.94	--	7.39	--	4.84	--
Portugal	2.49	--	8.79	--	6.30	--
Romania	0.88	--	8.73	--	7.85	--
Lithuania	1.52	--	6.80	--	5.27	--

Distributions are weighted by 1997 share of hours worked by ISIC Rev.4 industries for each country. Only countries with full information on real gross value added and hours worked are in the table (Belgium, Bulgaria, Croatia, Estonia, Hungary and Poland are not included due to this reason).

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	2.07	2.52	8.70	9.30	6.71	6.78
Mining	4.18	4.47	7.73	8.27	3.68	3.81
Food products	3.34	3.44	8.67	9.38	5.66	5.94
Textiles	2.68	2.91	7.70	8.31	5.31	5.39
Wood and Paper products	2.95	3.32	7.93	8.58	5.42	5.26
Chemicals & Other Mineral	3.63	3.77	9.07	9.21	5.70	5.44
Basic metals	3.14	3.37	8.31	9.28	5.61	5.90
Computer & Electronics	2.95	3.09	7.63	8.76	5.17	5.68
Machinery	3.04	--	7.62	--	5.07	--
Transport Equipment	3.20	3.37	7.57	8.68	4.84	5.31
Utilities	4.19	4.45	9.04	9.21	4.92	4.76
Construction	3.09	3.33	9.56	10.35	6.57	7.02
Education	3.28	3.47	9.43	10.23	6.24	6.76

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.[6]

[6] As mentioned before our database differs in the number of years – it began in 1997 – and countries – consider more 10 countries (Bulgaria, Czechia, Estonia, Croatia, Lithuania, Poland, Portugal, Romania, Slovenia and Slovakia) but we did not include Australia and South Korea due to incompatible data. 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, except for the variable Robot Density that are proprietary and as such, we used our own access to the same IFR database. Figure A2 in the Appendix also replicates Figures 2.A (left hand side) in GM.

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* (which is the used by GM).[7] The variation in the coefficient for robot density moves on the range of 0.56 – 0.97 (normalization by hours worked *by total employees*) and 0.55 – 0.80 (normalization by hours worked *by total persons engaged*), whereas GM estimates an interval of 0.36-0.57, using the normalization .

In terms of annual increases of labor productivity growth due to robotization, our numbers suggest an interval that ranges from 5.6, in the case of the country fixed-effects Ordinary Least Squares (OLS) regression, to 8.4 percentage points in the case of country fixed-effects Instrumental Variable (IV) estimation (Table 3).[8] In the same setting GM´s numbers translate into an acceleration on the range of 2.6-4.1 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 related to the use of less 4 years (1993-1996) than GM's and almost 50% more countries.

TABLE 3

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

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of Δ $(\#\frac{robots}{hours})/100$	0.555***	0.546***	0.451***	0.545***	-0.105	-0.002
	(0.091)	(0.093)	(0.086)	(0.094)	(0.084)	(0.087)
B. Instrumental Variable						
Percentile of Δ $(\#\frac{robots}{hours})/100$	0.965***	0.804***	0.565***	0.717***	-0.400***	-0.087
	(0.116)	(0.113)	(0.109)	(0.114)	(0.112)	(0.118)
First-stage F-statistic	220.6	239.7	220.6	239.7	220.6	239.7
Observations	269	256	269	256	269	256
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

[7] In the following Tables 3 to 5 one can observe evidence according to which 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 – see e.g. column (5) when comparing to column (6) in Tables 3 to 5.

[8] 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.

Robust standard errors in parenthesis. Regressions weighted by each industry's available initial 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 value: the proportion of labor productivity growth that came from value-added growth is at least 59%, when using hours worked by employees in the IV regression, and almost 100% when working with hours worked by persons engaged in the fixed-effects OLS regression.

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

In Table 4, we show the results for the whole sample, between 1997 and 2017, and observe that when compared with results in Tables 3, the effect of robotization on labor productivity growth is less pronounced than in the 1997-2007 period. We find that robots increase labor productivity growth in the interval 5.2 – 7.2 percentage points, where the lower bound comes from fixed-effects OLS estimation and the upper bound from fixed-effects IV estimation. When compared to the previous results, this relative decline in the annual effect of robotization in labor productivity is one of the main results we want to highlight and develop once we analyze the second subsample (2008-2017).

The upward movement in labor productivity growth seems to be driven more by the positive effects of robotization on value-added growth than on decreasing hours worked, since, in this case, this coefficient is not statistically significant. When we adjust variables by hours worked *by employees* (even columns in the tables), we observe again the importance of a reduction in the growth rate of hours worked to the growth in labor productivity increases. It is also important to point out that in the IV estimations the quantitative relevance of hours worked in the explanation of the productivity is now increased and it rivals, in magnitude, the contribution of robots to value added (column 5, IV estimation).

TABLE 4

Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked: Full period (1997-2017): OLS and IV Estimates

	$\Delta \ln (VA/H)$		$\Delta \ln (VA)$		$\Delta \ln (H)$	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.740***	0.503***	0.631***	0.591***	-0.109	0.088
	(0.111)	(0.130)	(0.111)	(0.109)	(0.104)	(0.102)
B. Instrumental Variable						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	1.070***	0.697***	0.532***	0.535***	-0.538***	-0.161
	(0.132)	(0.139)	(0.121)	(0.119)	(0.130)	(0.129)
First-stage F-statistic	361.9	397.1	361.9	397.1	361.9	397.1
Observations	252	241	252	241	252	241
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

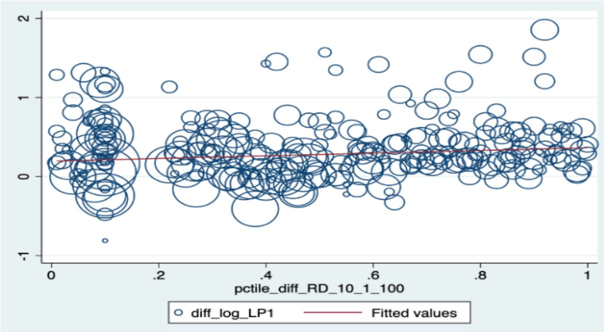
Robust standard errors in parenthesis. Regressions weighted by each industry's available initial share of hours within a country. Models 1,3 and 5 normalize variables by total hours worked by employees whereas models 2, 4 and 6 normalize variables by total hours worked by persons engaged.

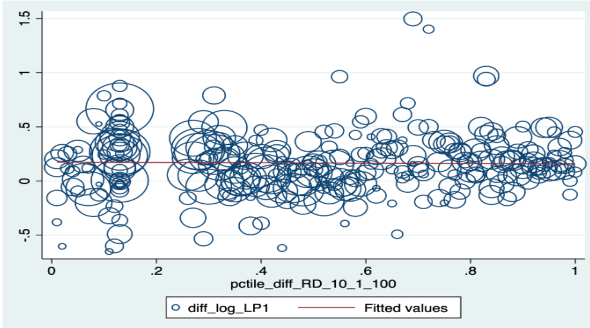
In fact, we want to explore this apparent slowdown in the effect of robotization when considering a much lengthier period. We wonder that this result comes from a much lower effect of robotization in the period coinciding with and after the financial crisis. This is the reason why we pin down the timeframe 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 possible to see from Figure 1 that robotization is more correlated to labor productivity growth in the period 1997-2007 than 2008-2017. The slope in the left-hand-side figure is +0.160 and it is -0.017 on the right-hand side figure.

FIGURE 1

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





Note: the size of the circles represents the weight of the sectors in the initial year also used in regressions

Between 2008 and 2017, the effect of robotization on labor productivity, although still positive and statistically significant, indicates a drop in the variation in log points by as much as 51% when we compare column 1 of Tables 3 and 5 and by as much as 75% when we compare columns 2 of both tables.

TABLE 5

Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked Second Period (2008-2017): OLS and IV Estimates

	$\Delta \ln (VA/H)$		$\Delta \ln (VA)$		$\Delta \ln (H)$	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of Δ $(\# \frac{robots}{hours})/100$	0.270***	0.133**	0.127**	0.055	-0.143***	-0.077
	(0.057)	(0.057)	(0.065)	(0.067)	(0.056)	(0.051)
B. Instrumental Variable						
Percentile of Δ $(\# \frac{robots}{hours})/100$	0.472***	0.280***	0.229**	0.098	-0.243***	-0.182***
	(0.089)	(0.085)	(0.095)	(0.091)	(0.089)	(0.074)
First-stage F-statistic	176.8	223.0	176.8	223.0	176.8	223.0
Observations	282	283	282	283	282	283
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis. Regressions weighted by each industry's available initial 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.

We estimate that robotization increases the growth rate of labor productivity in this period in the range of 1.3 to 2.8 percentage points in the main specification (even columns), much below the pattern observed in the initial sample, and below the pattern in the whole period. Therefore, the result obtained for the whole sample is strictly related to much smaller effect of robotization in annual productivity growth in the most recent 10-year period.

It is also interesting that, in some cases, as in part B of Table 5, 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 3 and 5 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 more than 90% between the two subsamples while the effect of robots on hours worked growth goes from statistically zero values in almost all the cases to negative and statistically significant, also in the most robust cases.

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. All in all the possibility to have a positive effect of robotization in hours worked is not supported by the data. 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).

In fact, 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. This result is also 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 general-purpose technologies, such as the massification of electricity and the use of steam engine did back in the 19th and early 20th century.

V. Robustness Checks in Median Cross-Section Analysis

In this Section, we comment in several results that we have obtained in different specifications which the majority is presented in the Appendix and the others may be supplied upon request. First the alternative use of two-way clustering (by both industry and country) of the standard errors (presented in Appendix A3) does not change the main result of the paper: the decrease in the effect of robotization from the first (1997-2007) to the second period (2008-2017). In fact, the use of the two-way clustered standard errors is a conservative approach as it typically – and in this case – yields higher standard-errors than when one-way clustering or no clustering at all are used. There are two fact worth mentioning concerning this robustness check: (i) the increase in the value-added is the only driver of robotization-led increase in labor productivity as hours worked become non-significant in both the whole period sample (1997-2017) as also in the first period (1997-2007) and (ii) in the second period, the robotization looses its statistical significance in increasing the labor productivity (measuring as proportion of hours worked *by persons engaged*) again highlighting the huge decrease in the effect of robotization in labor productivity in this second period.

A second major robustness check was the consideration of the terminal year of the sample in 2016 (presented in Appendix A4). This was made in order to allow the inclusion of more countries and thus increasing the sample size (from nearly 240-250 to 250-360) and the inclusion of important countries such as the UK. This analysis also confirms our main result: the decrease in the effect of robotization from the first (1997-2007) to the second period (2008-2016), both when we used robust standard-errors and when we used two-way clustered standard errors.

Results using more restricted samples of countries than the one used (that explore the whole availability of data) and that were more closely related to the sample used in GM all the results of the previous analysis are also confirmed. Again, we obtain a fall in the effect of robotization between from the first (1997-2007) to the second period (2008-2017). That more restricted samples were closer to the frontier countries in the robotization process. In those cases in the second period the negative effect of robotization on hours worked by people employed or engaged are even more significant than the effects presented above.[9]

VI. Quantile Regressions approach

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

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

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

[9] These results are supplied upon request.

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.

Below we present three 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 Fixed-Effects Regression									
Percentile of Δ $(\#\frac{robots}{hours})/100$	0.369***	0.285***	0.338***	0.390***	0.329***	0.299***	0.345***	0.358***	0.337***
	(0.087)	(0.077)	(0.086)	(0.100)	(0.090)	(0.091)	(0.102)	(0.099)	(0.100)
B. IV Quantile Regression									
Percentile of Δ $(\#\frac{robots}{hours})/100$	0.712***	0.709***	0.706***	0.705***	0.704***	0.703***	0.701***	0.698***	0.696**
	(0.159)	(0.127)	(0.111)	(0.117)	(0.130)	(0.147)	(0.179)	(0.236)	(0.287)
Observations	256	256	256	256	256	256	256	256	256
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 5% 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 oscillate until the 4th decile and starts to decrease thereafter until the 9th 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 7.4 percentage points for the least productive sectors and in nearly 7.2 percentage points for the most productive sectors.

TABLE 7

Changes in Robots Input and Growth on Productivity: Second 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 Fixed-Effects Regression								
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.292***	0.237**	0.193***	0.187***	0.153**	0.147**	0.153**	0.146*	0.054
	(0.121)	(0.100)	(0.074)	(0.072)	(0.063)	(0.064)	(0.062)	(0.079)	(0.106)
	B. IV Quantile Regression								
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.367***	0.354***	0.347***	0.341***	0.337***	0.331***	0.325***	0.317***	0.305**
	(0.103)	(0.080)	(0.074)	(0.075)	(0.078)	(0.087)	(0.099)	(0.120)	(0.150)
Observations	283	283	283	283	283	283	283	283	283
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. Firstly, most of the quantile coefficients in the second period are more than 50% lower than in the first 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. Secondly, the coefficients of higher quantiles of the labor productivity growth distribution lose statistical significance. In these second-period regressions, robotization increases productivity growth in 3.7 percentage points for the least productive sectors and in nearly 3.1 percentage points for the most productive sectors.

TABLE 8

Changes in Robots Input and Growth on Productivity: Full period (1997-2017): Quantile Regression and IV Quantile Regression

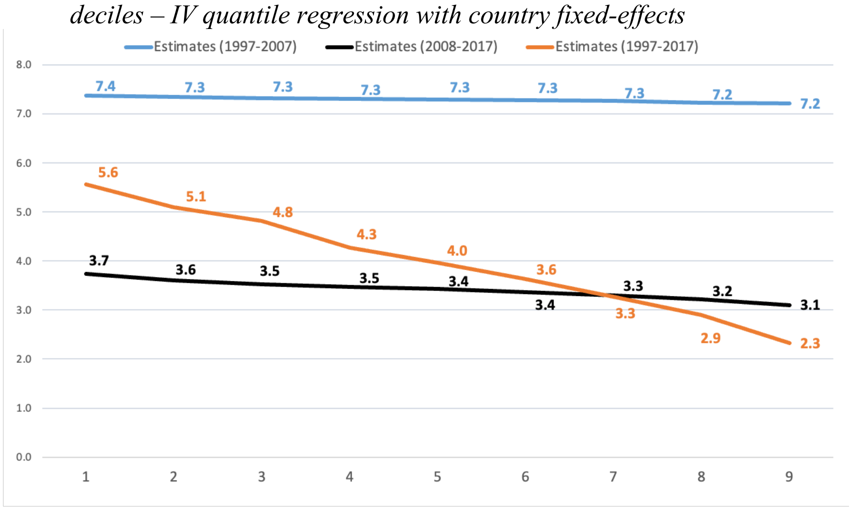
	Quantile coefficients								
	$\theta = .1$	$\theta = .2$	$\theta = .3$	$\theta = .4$	$\theta = .5$	$\theta = .6$	$\theta = .7$	$\theta = .8$	$\theta = .9$
	A. Quantile Fixed-Effects Regression								
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.813***	0.766***	0.620***	0.472***	0.434***	0.506***	0.405***	0.402***	0.402**
	(0.143)	(0.159)	(0.132)	(0.123)	(0.139)	(0.146)	(0.138)	(0.134)	(0.180)
	B. IV Quantile Regression								
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	1.083***	0.994***	0.940***	0.836***	0.778***	0.713***	0.644***	0.572***	0.459**
	(0.171)	(0.146)	(0.136)	(0.126)	(0.127)	(0.135)	(0.149)	(0.170)	(0.208)
Observations	241	241	241	241	241	241	241	241	241
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. In the whole sample the quantitative effects goes from 5.6 percentage points for the least productive sectors and in nearly 2.3 percentage points for the most productive sectors, meaning halving the effect from the first to the last decile, a higher variation in effects than that observed in each of the subperiods (see also Figure 2).

And just as the average model showed, the effects of robotization are significantly higher for the whole sample than for the initial period. 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.

FIGURE 2.
Changes in Robots Input and annual percentage points increase of Productivity by selected labor productivity deciles – IV quantile regression with country fixed-effects



From the higher quantiles (from the 6th onwards) 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. 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. It also encompasses the fact the elasticities of productivity towards robots decreases a lot during the whole period and much more than within each period.

6.2. Panel Data panel Regressions Approach

In this Section we extend the previous setup to panel data, both using Quantile Panel Data Country-Industry Fixed Effects and IV approaches. This should also act as a robustness check for our main conclusions so far. Now, instead of working with a limited range of cross-section observations, namely long-term growth rates for the dependent and explanatory variable, we use a panel of more than 6,000 observations to calculate yearly variations for labor productivity and robot density. In table 9, we lay out the coefficients of robotization for both models (fixed-effects and IV), starting with the country-industry fixed-effect approach that shows, again, a decreasing pattern along the main deciles of the labor productivity distribution, meaning that robotization has stronger effects in labor productivity for the least productive country-industry pairs. For this model, we create a dummy variable that assumes a value of zero for observations between 1997-2007 and a value of one for those between 2008-2017. In order to obtain quantile marginal effects of robotization for both periods, we interact this dummy with the percentile of robot density. The coefficients on the first row show the effects of robots on labor productivity for the period 1997-2007 (as the dummy takes the value 0 for those years) and, because the coefficient of the interaction between the dummy and the robotization variables is negative and statistically significant, the model corroborates the previous results that robotization loses capacity to accelerate labor productivity growth in recent years, with an approximately 5.6 percentage points yearly increase in labor productivity growth for the first decile all the way through a 2.4 percentage point increase for the ninth decile for the first period but going from 2.4 percentage points decrease towards an increase from 3.3 to 5.4 percentage points from the 7th to the 9th decile. The new result coming from this panel data approach is that in the second period (contrary to what happened in the first, the effect of robotization in labor productivity increases towards the most productive sectors. This points out that if some sectors are benefiting from robotization in this most recent period are those that are already the most productive ones. This can indicate that robotization are now contributing to increase inequality (even in wages), a result that is open to further investigation since it is obtained just in the panel approach.

In the same direction, the IV quantile regression uses pooled data to produce estimates for the structural quantile function. Our IV strategy is now a bit different from before, since we must accommodate the panel data features. Following Artuc et al. (2020), we interact the Replaceability Index with the initial level of GDP per capita for each country and the yearly Global Stock of Robots to produce a new IV that varies across the triplet country-industry-time.[10] The results can be seen in the lower half of table 9 and show the same decreasing pattern for the effects of robotization across the main deciles of labor productivity, going from roughly 12.8 percentage point increase in yearly labor productivity growth for the first decile down to roughly 3 percentage points for the 5th decile, going to nearly 0 in the 6th and 7th decile (as in this case this corresponds to nonsignificant coefficients) and reaching 9.4% percentage points decrease in yearly labor productivity for the 9th decile. These values are applied in the first period. Again, because the coefficient of the interaction between the dummy and the robotization variables is negative and statistically significant, the model corroborates the previous results that robotization loses capacity to accelerate labor productivity growth in recent years. Thus in the second period the marginal coefficient gives us the following information. From the 1st to the 4th decile we obtain positive and decreasing effects of robotization that go from 7.8 to 0.5 percentage points increase. Then from the 5th to the 9th decile the effects turn out to be negative going from 4 to 11.4 decrease in labor productivity. Thus our IV approach do not confirm the positive and increasing effects of robotization in labor productivity for the second period (2008-2017).

[10] In order to instrument the iteration variable we interact the described IV with the structural break.

TABLE 9

Changes in Robots Input and Growth on Productivity: Full sample (1997-2017)

	Quantile coefficients								
	$\theta = .1$	$\theta = .2$	$\theta = .3$	$\theta = .4$	$\theta = .5$	$\theta = .6$	$\theta = .7$	$\theta = .8$	$\theta = .9$
A. Quantile Fixed-Effects Regression with time trend with a structural Break (2008) and jackknife adjustment in the SE									
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.056***	0.049***	0.045***	0.042***	0.039***	0.037***	0.033***	0.029***	0.024**
	(0.011)	(0.007)	(0.008)	(0.005)	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
Structural Break (Dummy=1)× Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	-0.08***	-0.06***	-0.05***	-0.04***	-0.03***	-0.02***	-0.01	0.006	0.030***
	(0.009)	(0.008)	(0.007)	(0.007)	(0.005)	(0.007)	(0.004)	(0.007)	(0.007)
B. IV Quantile Regression with a structural Break (2008)									
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.128***	0.084***	0.062***	0.045***	0.030***	0.014	-0.008	-0.037**	-0.094***
	(0.014)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.014)	(0.016)	(0.021)
Structural Break (Dummy=1)× Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	-0.05***	-0.05***	-0.04***	-0.04***	-0.04***	-0.04***	-0.03***	-0.03***	-0.02**
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)
Observations	6,019	6,019	6,019	6,019	6,019	6,019	6,019	6,019	6,019

Robust standard errors in parenthesis.

FIGURE 3

Changes in Robots Input and annual percentage points increase of Productivity by selected labor productivity deciles – (i) Panel Data Country-Industry Fixed Effects coefficients and (ii) IV quantile coefficients

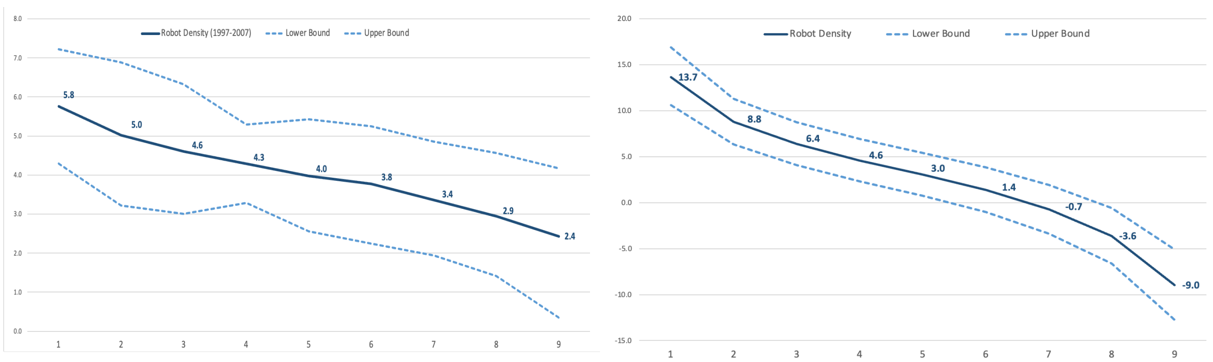
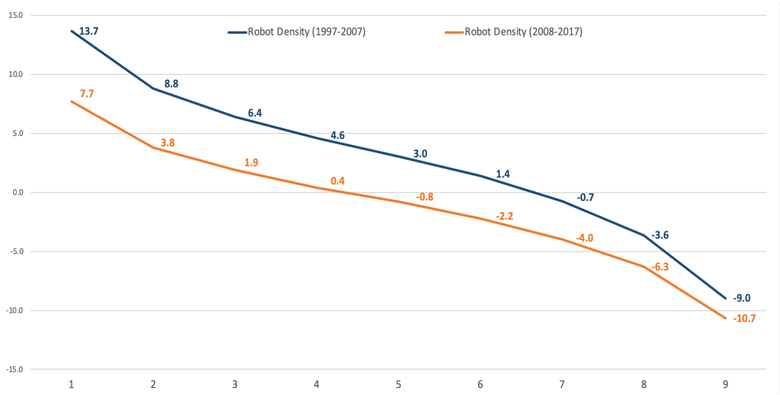


FIGURE 4

Marginal Effects for 1997-2007 and 2008-2017 with IV quantile coefficients



Quantitatively, the overall effect are in line with the obtained for the total cross-sectoral sample – compare with Table 8 and Figure 2. Figure 3 shows the coefficient and the respective confidence intervals for the direct effect and Figure 4 shows the marginal effects for both periods. Most importantly, the panel approach confirms the main result of the paper: the effect of robotization seems to be clearly lower in the second more recent period (2008-2017) than in the previous one (1997-2007).

It is worth noting that inserting an iteration between the trend and the Robot Density percentile, we would obtain: (i) a positive, significant and decreasing throughout the distribution marginal effect of the percentile of the robot density and (ii) a negative and significant effect of time in that effect. This highlights that in panel data, additional to a significant difference between periods that we highlighted, the results indicate that the marginal effect of robot density may have decreased *year by year* throughout this period (1997-2017). This result is obtained both with a quantile fixed-effects regression and with an IV regression similar to both specifications shown in Table 9.

VII. Conclusion

In this paper we analyze how 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. When compared to existing evidence we analyze a broader sample both in the time dimension and in the country dimension. In fact we add the most recent 10 year data and more than 10 countries to those analyzed by Graetz and Michaels (2018).

We obtain the effects of robotization on labor productivity felt between the first 10 years of the sample (1997-2007) and the last 10 years (2008-2017). Quantitatively the effects more than halved. In the most robust cross-sectional analysis, an increase in a percentile of the robot density implied a 8.4 percentage points increase in the labor productivity in the first period and 2.8 percentage points increase in the labor productivity in the second 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. Concerning the effect on hours worked while in the first period they tend not to decrease due to robotization, in the second period they seem to become more sensitive to robotization. A positive effect of robotization on hours worked is certainly dismissed by data.

We also conducted a quantile regression analysis (both on cross-sectoral and panel data) 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 tend to be more prominent in the higher quantiles. In a final exercise we present panel data regressions which by definition analyze the effects year by year. These regressions clearly confirm the fall in the effects of robotization in labor productivity in the second period when compared to the first one and for the most robust specification showed negative returns to robotization for the most productive deciles.

These 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 - Acemoglu and Restrepo (2019) and Acemoglu et al. (2020) - 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.

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2), 3-30.

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

Acemoglu, D., & Restrepo, P. (2022). Demographics and automation. *The Review of Economic Studies*, *89(1)*, 1-44.

Acemoglu, D., Manera, A. & Restrepo, P. (2020). Does the U.S. Tax Code Favor Automation? *Brookings Papers on Economic Activity*, Spring 2020 Edition.

Autor , D. H., F. Levy, and R. J. Murnane . (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics 118(4)*, 1279-1333.

Autor, D., C. Goldin, and L.F. Katz (2020). Extending the race between education and technology. *AEA Papers and Proceedings 100*, 347-51.

Artuc, E., Bastos, P., & Rijkers, B. (2020). *Robots, tasks, and trade* (REM Working Paper No. 0118-2020). Research in Economics and Mathematics.

Graetz, G., & Michaels, G. (2018). Robots at work. In *Review of Economics and Statistics 100(5)*, 753–768).

Gordon, R. J. (2015). Secular stagnation: A supply-side view. *American economic review*, *105(5)*, 54-59.

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

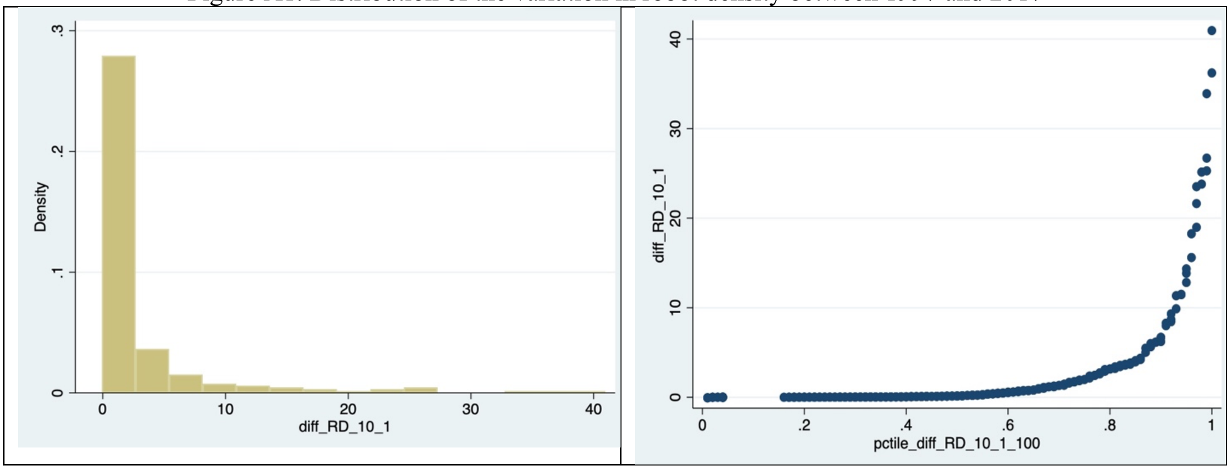
Machado, J. A. F., & Santos Silva, J. M. C. (2019). Quantiles via moments. *Journal of Econometrics*, *213*(1), 145–173.

Sequeira, T, P. Gil and O. Afonso (2018) Endogenous growth and entropy, *Journal of Economic Behavior & Organization*, 154: 100-120.

Zeira, J. (1998). Workers, machines, and economic growth. The Quarterly Journal of Economics, 113(4), 1091-1117.

A1. Distribution of Robot Density

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



A2. Replication of the GM main results

Table A2a. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (1993-2007): OLS and IV Estimates – without country trend – comparison with GM

	$\Delta \ln (VA/H)$		$\Delta \ln (VA)$		$\Delta \ln (H)$	
	Current work	GM	Current work	GM	Current work	GM
A. OLS						
Percentile of Δ (# $\frac{robots}{hours}$)/100	0.330***	0.359***	0.385***	0.336***	0.055	-0.023
	(0.125)	(0.106)	(0.135)	(0.117)	(0.116)	(0.114)
B. Instrumental Variable						
Percentile of Δ (# $\frac{robots}{hours}$)/100	0.877***	0.833***	0.619***	0.545***	-0.258	-0.289
	(0.198)	(0.188)	(0.159)	(0.155)	(0.175)	(0.169)
First-stage F-statistic	124.3	93.7	124.3	93.7	124.3	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 A2b. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (1993-2007): OLS and IV Estimates – with country trend – comparison with GM

	$\Delta \ln (VA/H)$		$\Delta \ln (VA)$		$\Delta \ln (H)$	
	Current work	GM	Current work	GM	Current work	GM
A. OLS						
Percentile of Δ (# $\frac{robots}{hours}$)/100	0.567***	0.572***	0.647***	0.602***	0.079	0.03
	(0.131)	(0.118)	(0.138)	(0.121)	(0.104)	(0.099)
B. Instrumental Variable						
Percentile of Δ (# $\frac{robots}{hours}$)/100	0.918***	0.873***	0.688***	0.607***	-0.230	-0.266
	(0.161)	(0.157)	(0.142)	(0.143)	(0.160)	(0.155)
First-stage F-statistic	161.9	152.6	161.9	152.6	161.9	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.

TableA2c. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (1993-2007): OLS and IV Estimates – without country trend

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	
	Current work	GM	Current work	GM	Current work	GM
A. OLS						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.330	0.359	0.385*	0.336*	0.055	-0.023
	(0.253)	(0.230)	(0.190)	(0.180)	(0.230)	(0.230)
B. Instrumental Variable						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.877*	0.880*	0.619**	0.570**	-0.258	-0.300
	(0.504)	(0.500)	(0.286)	(0.370)	(0.542)	(0.530)
First-stage F-statistic	124.3	93.7	124.3	93.7	124.3	93.7
Observations	238	238	238	238	238	238
Country Trend	No	No	No	No	No	No

Two-way cluster (Country and Industry) standard errors in parenthesis. Regressions weighted by each industry's 1993 share of hours within a country.

Table A2d. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (1993-2007): OLS and IV Estimates – with country trend

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	
	Current work	GM	Current work	GM	Current work	GM
A. OLS						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.567*	0.572*	0.647**	0.602**	0.079	0.03
	(0.288)	(0.27)	(0.253)	(0.230)	(0.260)	(0.250)
B. Instrumental Variable						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.918*	0.910*	0.688**	0.640**	-0.230	-0.280
	(0.487)	(0.490)	(0.322)	(0.400)	(0.530)	(0.520)
First-stage F-statistic	161.9	152.6	161.9	152.6	161.9	152.6
Observations	238	238	238	238	238	238
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Two-way cluster (Country and Industry) standard errors in parenthesis. Regressions weighted by each industry's 1993 share of hours within a country.

A3. Estimations with two-way clustered standard-errors

Table A3.1 Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked: First period (1997-2007): OLS and IV Estimates

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.555***	0.546**	0.451***	0.545***	-0.104	-0.002
	(0.194)	(0.214)	(0.159)	(0.183)	(0.202)	(0.249)
B. Instrumental Variable						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.965***	0.804***	0.565**	0.717***	-0.400	-0.087
	(0.280)	(0.320)	(0.234)	(0.250)	(0.296)	(0.393)
First-stage F-statistic	220.6	239.7	220.6	239.7	220.6	239.7
Observations	269	256	269	256	269	256
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Two-way clustered standard errors in parenthesis. Regressions weighted by each industry's available initial 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 A3.2. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked: Full sample (1997-2017): OLS and IV Estimates

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	

	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of Δ ($\#\frac{robots}{hours}$)$/100$	0.740***	0.503	0.631**	0.591**	-0.109	0.088
	(0.195)	(0.346)	(0.246)	(0.245)	(0.263)	(0.292)
B. Instrumental Variable						
Percentile of Δ ($\#\frac{robots}{hours}$)$/100$	1.070***	0.697	0.532**	0.535**	-0.538	-0.161
	(0.302)	(0.442)	(0.231)	(0.252)	(0.368)	(0.419)
First-stage F-statistic	361.9	397.1	361.9	397.1	361.9	397.1
Observations	252	241	252	241	252	241
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Two-way clustered standard errors in parenthesis. Regressions weighted by each industry's available initial 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 A3.3 Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked Second Period (2008-2017): OLS and IV Estimates

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of Δ ($\#\frac{robots}{hours}$)$/100$	0.269***	0.133	0.127	0.055	-0.143	-0.077
	(0.080)	(0.127)	(0.128)	(0.138)	(0.097)	(0.086)
B. Instrumental Variable						
Percentile of Δ ($\#\frac{robots}{hours}$)$/100$	0.472***	0.280	0.229	0.098	-0.243	-0.182
	(0.167)	(0.207)	(0.199)	(0.197)	(0.268)	(0.194)
First-stage F-statistic	176.9	223.0	176.9	223.0	176.9	223.0
Observations	270	283	270	283	270	283
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Two-way clustered standard errors in parenthesis. Regressions weighted by each industry's available initial 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.

A4. Regressions with observations until 2016

TableA4.1. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked Full Sample (1997-2016): OLS and IV Estimates

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of Δ ($\#\frac{robots}{hours}$)$/100$	0.710***	0.498***	0.589***	0.535***	-0.134	0.013
	(0.105)	(0.122)	(0.103)	(0.101)	(0.098)	(0.094)
B. Instrumental Variable						
Percentile of Δ ($\#\frac{robots}{hours}$)$/100$	1.056***	0.696***	0.443***	0.435***	-0.612***	-0.271**
	(0.128)	(0.132)	(0.115)	(0.112)	(0.130)	(0.124)
First-stage F-statistic	363.1	405.1	391.3	397.2	383.7	387.9
Observations	267	254	267	254	267	254
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.

Table A4.2. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked Second Period (2008-2016): OLS and IV Estimates

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)

	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.260***	0.141***	0.124**	0.055	-0.141***	-0.092**
	(0.054)	(0.051)	(0.062)	(0.060)	(0.051)	(0.045)
B. Instrumental Variable						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.420***	0.237***	0.152*	0.047	-0.265***	-0.189***
	(0.080)	(0.146)	(0.089)	(0.082)	(0.084)	(0.068)
First-stage F-statistic	208.5	266.4	208.5	266.4	208.5	266.4
Observations	308	309	308	309	311	312
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Two-way cluster (Country and Industry) 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 A4.3. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (1997-2016): OLS and IV Estimates

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.710***	0.498	0.589**	0.535**	-0.121	0.037
	(0.185)	(0.331)	(0.227)	(0.225)	(0.254)	(0.274)
B. Instrumental Variable						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	1.056***	0.696*	0.443**	0.435*	-0.612	-0.261
	(0.299)	(0.425)	(0.222)	(0.238)	(0.387)	(0.422)
First-stage F-statistic	363.1	405.1	363.1	405.1	363.1	405.1
Observations	267	254	267	254	267	254
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Two-way clustered 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 A4.4. Changes in Robots Input and Growth on Productivity, Value Added and Hours Worked (2008-2016): OLS and IV Estimates

	Δ ln (VA/H)		Δ ln (VA)		Δ ln (H)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.260***	0.141	0.124	0.055	-0.136	-0.086
	(0.066)	(0.109)	(0.109)	(0.122)	(0.090)	(0.072)
B. Instrumental Variable						
Percentile of $\Delta\ (\#\frac{robots}{hours})/100$	0.420***	0.237	0.152	0.047	-0.268	-0.189
	(0.139)	(0.177)	(0.204)	(0.183)	(0.269)	(0.185)
First-stage F-statistic	208.5	271.6	208.5	271.6	208.5	271.6
Observations	308	309	308	309	311	309
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes

Two-way clustered 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.