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Automation, Digitalization, and Income Inequality in Europe

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Abstract

We analyze the impact of industrial robots as well as investment in computing equipment and digital technologies on different indicators of income distributions. Our data covers selected West European EU economies from 2004 to 2017. We try to shed light on the underlying dynamics of technological advances on inequality. The results suggest that robot density is associated positively with income inequality, while no robust evidence is found for the computing equipment and digital technologies. In particular, the income shares of the bottom 20 and 50 percent decreases with automation, while the income shares of the top 10 and 1 percent increases, which supports the job and wage polarization hypothesis. This is especially important for policy formulations after the pandemic, because current rapid automation efforts can potentially have significant long-term implications for the labor market.

1. Introduction

Ever since the First Industrial Revolution, advances in automation technologies have led to a change in human labor compositions and sparked fears in workers of being replaced and their welfare decreasing (Brynjolfsson & McAfee, 2012; Robinson & Acemoglu, 2012; Prettner & Bloom, 2020). Even though the negative effect on the job market has been offset so far by job creation in other sectors in the past, they can be associated with significant distributional effects. As far as the jobs are mostly shifted from manual-intense sectors towards service sectors (Autor, 2015), the mismatch between qualification, skills, and other employee characteristics may also be important. Insights and discussions on the effects of technologies on labor are especially urgent in the wake of the coronavirus pandemic, which has accelerated automation efforts rapidly.

Technological progress in the 21st century is not only characterized by the introduction of industrial robots and machinery but also by an increase in digital

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technology, such as computer software and artificial intelligence, that enables new technologies to not only replace manual but also sophisticated labor. Many formerly labor-intense tasks as well as cognitive tasks can now be partially or fully automated and are successively adapted by companies. A recent study about the future of employment suggests that 47 percent of current jobs are or can be automatable in the near future (Frey & Osborne, 2017). This causes high levels of anxiety about automation and other areas of technological progress. The Eurobarometer survey shows that 72 percent of respondents agreed with the statement that “robots and artificial intelligence steal peoples’ jobs” (European Commission, 2017).

Due to its major social significance, the question arises of how automation will impact the future of work and if it will impact overall employment levels, wage distribution and ultimately overall welfare. A clearer understanding of the effects of automation can help companies, policymakers and workers to better adjust to the changing situation.

Even though the impact of automation on employment levels, wage distribution and inequality has been the topic of academic research in recent years, the estimated effects are ambiguous. While some economic research finds that industrial robots are negatively correlated with total employment (Acemoglu & Restrepo, 2017b; Carbonero et al., 2018; Kaltenberg & Foster-McGregor, 2019), other studies find a positive correlation (Acemoglu & Restrepo, 2019; Chiacchio et al., 2018; Dauth et al., 2017), and some find no significant correlation (Klenert et al., 2020). A comprehensive analysis of the macroeconomic consequences of automation has been conducted by Prettner and Bloom (2020).

Most researchers (Acemoglu & Restrepo, 2016; Chiacchio et al., 2018; Goos et al., 2009) use IFR data on industrial robots. This work aims to contribute to existing research by particularly focusing on further specifying research on automation by distinguishing between robotization and digitalization to gain a more nuanced insight into ongoing forces. This can help to better understand the dynamic relationships at play. It is also important for predictions how automation and digitalization can impact society after the COVID-19 pandemic, which lead to an increase of intensity of digitalization and automation.

The analysis includes 13 European countries and covers the period between 2004 and 2017. The data comes from the International Federation of Robotics (IFR), EU KLEMS, and Eurostat. Our results suggest that *robot density* rises income inequality. In comparison, we do not find any robust evidence for our indicator of *digitalization*.

Thereby, this work is structured as follows: The next section presents an historical overview as well as a literature review on the impact of industrialization, digitalization, and automation on employment and inequality. Section 3 describes the data set. We also analyze the impact of automation technology (using the proxy operational robots stock) and digitalization efforts (using equipment and digital technologies as a proxy) on inequality measures. Moreover, we discuss the results of the empirical model and robustness analysis. Finally, section 4 summarizes and concludes.

2. Literature Review

2.1 Historical Overview of Automation Milestones

Concerns about technological unemployment have been raised by influential economists such as Ricardo and Keynes. They argued that workers are being replaced by machines, which leads to a decrease in labor demand (Acemoglu & Restrepo, 2017b). These fears were demonstrated by workers who have been concerned about being replaced by automated technology ever since the First *Industrial Revolution*. Early industrial machines replaced labor previously conducted by unskilled worker on a large scale, which was leading to widespread fears and protests. At the same time, also the elites feared social and political instability as a result of technical progress. Notably, Queen Elizabeth I was so worried about the employment impact of William Lee's knitting machine in 1589 that she refused to grant him a patent (Robinson & Acemoglu, 2012). The threat to their livelihoods even led workers to destroy hundreds of machines with sledgehammers, even though this was punishable by death (Klenert et al., 2020). However, the long-term consequences of this technological revolution were in fact beneficial for the workers. As machines became cheaper relative to skilled labor, production became more capital intensive. As a result, prices for goods decreased and real income increased. The raised productivity generated new wealth and more jobs, so even unskilled workers benefitted in the long-run (Lindert & Williamson, 2016). Thus, the real impact of automation is determined by the two competing effects of technological progress: First, the substitution of labor effect, which requires workers to reallocate their labor supply, and second the capitalization effect, which refers to new companies entering into high-productive industries (Katz & Margo, 2013).

The beginning of the 20th century was characterized by the *Electricity Revolution*. The emergence of assembly lines and other types of machinery were technological breakthroughs which changed the man/machine labor relationship. This led to a decrease in the demand for relatively unskilled manual workers and an increase in the demand for relatively high skilled production workers to operate the machinery. Furthermore, the transport revolution lowered costs of shipping goods domestically and internationally. This eroded local monopoly power, increased competition, and compelled firms to raise productivity through automation. Additionally, the demand for white-collar nonproduction workers was heightened by the increasing number and complexity of managerial and clerking tasks (Katz & Margo, 2013).

The middle to late 20th century was characterized by the *Computer Revolution*. The decline in the cost for computational power and equipment as well as the introduction of the internet in the 1990s made certain jobs such as typists and telephone operators largely redundant, while it led to an overall increased demand for educated labor complementary to the equipment. This increased capital-skill complementarity due to the adoption of computers and information technology resulted in a higher demand for high-skilled labor and changed the white-collar labor force (Goldin & Katz, 2007).

As this paper analyses 13 European countries, the crowding out effect of labor by robots in Europe is described in more detail for the last 50 years. Since the 1970s, labor market development in Europe has been defined by deindustrialization, with the constant decline of manufacturing employment and a corresponding increase in service sector employment. The share of European employees working in the manufacturing sector has decreased from around 20-30 percent in the 1970s to around 10-20 percent today (Klenert et al., 2020). Graetz and Michaels (2015) study the effects of automation on the European labor market, using data from the IFR on the deliveries of multipurpose manipulating industrial robots over the period 1993-2007. Their results show that robot density has increased by around 150 percent between 1993 and 2007. The sectors and countries which saw a particularly strong increase in robotization were the transport equipment, chemicals and metal sectors in Germany, Denmark, and Italy, which also experienced the largest gains in labor productivity. They did not find increased robot density to be associated with significant changes in employment levels, but they found the overall effect of robot use on wages to be positive. Overall, this shows that on several occasions throughout history technological breakthroughs have had an impact on the labor market and inequality.

2.2 Empirical Literature on Labor Displacement through Robots

Economic research that studies the effect of industrial robots on employment can be split into two groups. First, authors who use aggregated data from the International Federation of Robotics as a source. These tend to find a negative correlation between robots and low-skilled employment. Second, studies using micro-economic data. These tend to find a neutral or positive correlation between low-skill employment and the use of robots, suggesting a complementarity relationship between robots and low-skilled jobs (Klenert et al., 2020).

The routine-replacing technological change hypothesis (RRTC) outlines the labor altering effects of automation. Gregory et al. (2016) show that the reduction of labor demand in one sector through robotization is offset by the creation of additional labor demand through the product demand effect. Declining capital costs reduce prices and raise product demand including demand spillovers. In particular, they show positive quantitative net job effect (11.6 million jobs) as a result of automation for 238 regions across 27 European countries.

Acemoglu and Restrepo (2019) find a negative effect of robots on employment and wages in the US. Similarly, Chiacchio et al. (2018) found an overall negative impact of robotization on employment and wages in six European countries. Dauth et al. (2017) report that the negative impact on industrial employment of each robot destroying two manufacturing jobs in Germany is offset by spillovers into other sectors which lead to the creation of new jobs. The overall effect on total employment is thus neutral when employment spillovers between sectors are accounted for. A neutral effect of technology on employment is also found by Klenert et al. (2020) in their industry-level study across the European level in the last three decades. These studies show that there is not yet an agreement in current research on the effects of the technology on the labor market, with different studies finding diverging effects. This indicates that more research is needed to understand the process of creative destruction resulting from automation.

2.3 Skill-Biased Technological Change and Job Polarization

Researchers studying the impact of technology on the labor market emphasize the role played by *skill-biased technical change* (SBTC), which states that technology is biased in favor of skilled workers and against unskilled workers as machinery replaces manual labor. According to this approach, as technological progress favors relatively skilled workers, it results in a higher skill premium, decreased employment and wages for less skilled workers, which in turn results in higher inequality (Machin & van Reenan, 1998). Autor et al. (1998) have found evidence that 30 to 50 percent of the relative demand in growth since the 1970s can be explained by the introduction of computer technology in the US. Machin and van Reenen (1998) have found a positive relationship between R&D expenditure and relative demand for skilled workers and thus evidence for SBTC in seven OECD countries. However, current research has taken a more nuanced approach by focusing on the nature of tasks, *routine* and *non-routine.* This expands the understanding of the impact of technology on jobs along the whole spectrum of wages. Routine labor tasks are step-by-step procedures or rules which are increasingly more easily replaced by machinery while non-routine labor tasks are not yet replaceable (Autor et al., 2006).

Goos and Manning (2007) analyze the *job polarization* effects. According to their research, the routine labor tasks can be increasingly substituted by technology. Affected are jobs such as manual jobs and bookkeeping jobs which require precision. Goos et al. (2009) find evidence for this pattern, i.e. a disproportionate increase in high and low-paid employment due to routine-biased change in 16 Western European countries over the period 1993-2010. High-paying managerial and professional jobs in particular have seen the most rapid increases in their employment shares, while employment shares with a median wage have declined. Autor and Dorn (2013) confirm the job polarization hypothesis and find evidence of a U-shaped distribution in the relationship between skill level and employment growth between 1980 and 2005 in the US.

While many workers fear the employment and displacement effects of automation, current research shows that workers will be sorted into new jobs in the long-run, resulting in only short-lived unemployment effects. However, the composition of labor based on their skill-level has changed dramatically over the past decades, leading to a higher share of low and high-skill workers which, in turn, might have an impact upon income inequality.

2.4 Automation and Digital Technology

While there has been extensive research on job and wage polarization due to robots replacing middle-skill workers (Acemoglu & Restrepo, 2017a; Goos et al., 2009), the new changes in the structure of automation, namely digital information and communication technology (ICT), have received less attention.

According to the job polarization hypothesis, high-skilled worker with their cognitive, non-routine jobs are harder to replace because their tasks are more complex, requiring judgment, problem-solving, analytical skills and various soft skills. But in recent years, digital technology has been increasingly able to not only replace manual labor but also cognitive tasks, turning non-routine tasks into defined problems. This led to a desire for software to automate them. Brynjolfsson and McAfee (2012) argue that digital technologies, contrary to other major technology changes in the past, have stronger labor replacing forces.

Chui et al. (2016) document that a significant percentage of the activities performed, including highly qualified tasks (for example, financial planners, physicians, and senior executives), can already be automated by means of current technology. Byrne and Corrado (2017) argue that ICT has entered a fourth major era (following machines, computers and the Internet) in which mobile and cloud platforms are becoming the predominate means organizations use to interact. This increase in the implementation of technology in the workfare in recent years is due to the decline in relative ICT prices, allowing ICT equipment to be more financially accessible to firms. Big data and its complementary technologies have a comparative advantage to human labor, insofar as it is scalable - computers being better for those large calculations required in using large datasets, and also better able to detect patterns. Another advantage of computers is the absence of human bias. Healthcare, judicial matters, financial services and fraud detection are areas where this is of great importance (Brynjolfsson & McAfee, 2012). Kaltenberg and Foster-McGregor (2019) find that digital automation can largely explain rising inequality within European countries, with the top 50 percent of the distribution profiting the most. This shows the increasing importance not only of industrial robots that have increased productivity in industrial production so far, but also of ICT affecting the labor process.

3. Empirical Analysis

3.1 Data

The robotization indicator used in this analysis comes from the World Robotics database, which is compiled by the IFR. This data set is frequently used for automation research (see Acemoglu & Restrepo, 2017b; Carbonero et al., 2018; Graetz & Michaels, 2018; Klenert et al., 2020). The IFR data covers the stock of operational robots between 2004 and 2017 for 13 EU countries (IFR, 2018). IFR (2020) defines robots in line with ISO 8373:2012 as an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed or mobile (see Table A1 in the Appendix for full definition of robots by ISO and the IFR).

To obtain a relative measure of the degree of robot adoption independent of the size of an economic sector, the IFR data is divided by the number of employed persons to measure the number of industrial robots per thousand workers by country. The indicator is labeled as “robot density” and defines the number of robots per 10,000 employees in each year.

For the ICT investment share as percentage of total assets, the EU KLEMS database is used. We use ICT equipment, which is defined as the sum of computing equipment, communication equipment, computer software and databases divided by total assets. The variable depicts the share of ICT equipment in overall tangible and intangible assets (Jäger et al., 2019).

For the dependent variables, we use the Eurostat Database as well as the World Inequality Database (WID). The indicators for income inequality include the *gini coefficient* before social transfers, the percentage of people at *poverty risk*, the national income shares of the *bottom 20 percent* and *bottom 50 percent*, the *quantile ratio*, the *top 10 percent* and *top 1 percent*, as well as the share of people earning more than *130 percent of the median income*.

To control for causes that might impact income inequality, as identified in literature (Acemoglu & Restrepo, 2017b; Piketty, 2015), further variables are included in the model. These include the *shares of low and high-level education* in the population to test the theory of job and wage polarization, the *logarithm of GDP per capita* controls for welfare differences, *growth of imports* to control for offshoring, *trade union density* is used to control for the bargaining power of the labor force, and *government expenditure as percentage of GDP* shows for different budgets at the country level which can be used for redistribution within the society (see Table A2 in Appendix for definition of the analyzed variables).

Table 1 shows the descriptive statistics presents for the variables used in this study. The dataset represents a nearly balanced data set with eight indicators of inequality as well as eight control variables for 13 European countries[1] and covers the year 2004-2017. The European countries included were selected based on the similarity of their economic systems and the availability of the data.

Table 1 Summary Statistics

	Obs.	*mean*	*st.dev.*	*min*	*max*
gini	175	49.743	4.199	43.200	61.600
poverty risk	161	21.699	5.253	13.900	36.000
first quantile	161	11.273	1.395	8.500	13.600
bottom 50%	177	21.989	2.172	17.320	26.820
quantile ratio	161	4.720	1.000	3.310	6.960
top 10%	177	32.784	2.754	28.050	39.660
top 1%	177	10.070	1.812	6.270	13.450
130median	158	28.436	2.912	22.000	34.500
robot density	177	14.648	9.871	0.137	45.422
ICT investment	164	11.529	3.556	2.950	20.534
low education	177	33.613	12.500	17.700	73.700
high education	177	25.311	6.872	10.000	39.500
GDP per capita	163	32390.982	9446.448	14520.000	57020.000
import growth	177	3.518	6.709	-20.354	33.164
trade unions	160	37.131	22.171	8.500	82.400
government exp.	163	48.851	5.816	28.200	65.100

Source: Own estimation.

3.2 Main Results

We analyze the effect of *robot density* and *ICT investment share* on different measures of inequality. For our estimation we use the following fixed effects regression model:

[1] Our sample consists of the following EU countries: *Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherland, Portugal, Sweden, and Spain.*

$$inequality_{it} = \beta_0 + \beta_1 robots_{it} + \beta_2 ICT_{it} + \sum_{k=1}^{K} \gamma_k \, x_{it} + \alpha_i + \theta_t + \varepsilon_{it}, \qquad (1)$$

where $inequality_{it}$ is proxied by eight different indicators of inequality. The variable $robots_{it}$ denotes robotization per employment, the variable ICT_{it} shows *ICT investment share as percentage of total assets*, while x_{it} denotes k additional control variables: *Low and highly educated population*, *GDP per capita*, *growth of imports*, *trade union density*, and *government expenditure as percentage of GDP*. The parameters α_i and θ_t present *country and time-fixed effects*, respectively. Finally, the error term ε_{it} represents all disturbances.[2]

Table 2 shows our baseline results. For the interpretation we have to keep in mind that the signs for *first quantile* and *bottom 50 percent*, which show the income share of low-income population, are opposite (i.e. coefficients for automation and digitalization are expected to be negative) in comparison to the other variables.

Table 2 The Impact of Robot Density on Different Measures of Inequality

	gini	*poverty risk*	*first quantile*	*bottom 50%*	*quantile ratio*	*top 10%*	*top 1%*	*130 median*
robot density	0.421***	0.249***	-0.076***	-0.148**	0.051***	0.203**	0.171**	0.222***
	(0.160)	(0.068)	(0.022)	(0.065)	(0.017)	(0.101)	(0.068)	(0.056)
low education	-0.250***	-0.106	-0.007	0.047	0.002	-0.087	-0.102**	-0.030
	(0.091)	(0.133)	(0.031)	(0.048)	(0.029)	(0.063)	(0.041)	(0.055)
high education	-0.120	0.044	0.011	0.139***	-0.001	-0.236**	-0.159**	-0.113**
	(0.097)	(0.155)	(0.033)	(0.042)	(0.029)	(0.093)	(0.070)	(0.056)
GDP per capita	-20.509***	-12.733***	0.122	-1.292	-0.371	2.642	-2.675	0.924
	(3.775)	(3.397)	(0.767)	(1.520)	(0.641)	(2.568)	(2.348)	(1.374)
import growth	0.017	0.014	0.008	-0.009	-0.003	0.025*	0.029*	0.007
	(0.033)	(0.010)	(0.006)	(0.008)	(0.004)	(0.015)	(0.016)	(0.011)
trade unions	-1.055***	-0.157	0.041	0.056	-0.010	0.103	0.035	-0.063*
	(0.162)	(0.114)	(0.032)	(0.040)	(0.023)	(0.072)	(0.058)	(0.033)
government	0.182**	0.050	-0.005	-0.012	0.005	-0.079***	-0.090***	0.026
	(0.074)	(0.040)	(0.012)	(0.024)	(0.010)	(0.030)	(0.023)	(0.025)
observations	144	144	144	146	144	146	146	141
adjusted R^2	0.561	0.269	0.160	0.210	0.039	0.246	0.227	0.273

Notes: Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Source: Own estimation.

Table 2 indicates that in terms of inequality, the coefficient of *robot density* has expected signs: The specification with the *Gini coefficient* and *poverty risk* as dependent variable show a positive and statistically significant effect. A negative and statistically significant effect on income is shown for the *bottom 20 percent* and *bottom 50 percent* of the population. A positive and statistically significant effect is estimated for the *quantile ratio*, as well as the *top 10 percent*, *the top 1 percent* and

[2] We use the "plm" package of the Data analysis software "R". To reduce endogeneity a fixed effects model is used to get rid of unobserved, time and country characteristics.

the people with an *income 130 times above the median*. Hence, *robot density* is generally associated with higher inequality. For example, the increase of robotization by its one standard deviation increases the *Gini coefficient* by 4.2 percentage points.[3]

It is particularly interesting to note that the income share of the bottom 20 and 50 percent decreases with automation, while the income shares of the top 10 and 1 percent increase. This supports the job and wage polarization hypothesis.

Finally, we can see that the control variables have expected signs, but they are less robust than the core variables. Countries with *lower levels of education* tend to have lower inequality as proxied by the *Gini coefficient*. More importantly, *high education levels* increase the income share of the *bottom 50 percent* of the population, thus reducing inequality. Similarly, *higher education levels* decrease the income share of the *top 10 percen*t and *top 1 percent*. *Growth of GDP per capita* and *trade union density* tend to lower inequality measured by the *Gini coefficient*. *Import growth* is only marginally positively significant for the *top 10 percent* and *top 1 percent*. Finally, *government expenditure as percentage of GDP* is associated with higher inequality according in the specification for the *Gini coefficient*. This shows that fiscal policies do not lower the levels of inequality in general. Nevertheless, the results for the specification for *top 10 percent* and *top 1 percent* confirm that *government expenditures* reduce the income shares of the rich through redistribution.

Table 3 The Impact of Robot Density & Digitalization on Diff. Measures of Inequality

	gini	***poverty risk***	***first quantile***	***bottom 50%***	***quantile ratio***	***top 10%***	***top 1%***	***130 median***
robot density	0.412^{***}	0.171^{**}	-0.064^{***}	-0.134^{**}	0.036^{***}	0.215^{**}	0.174^{***}	0.234^{***}
	(0.123)	(0.085)	(0.019)	(0.067)	(0.013)	(0.102)	(0.064)	(0.055)
ICT investment	0.032	0.278	-0.040	-0.051	0.053	-0.047	-0.011	-0.045
	(0.281)	(0.178)	(0.064)	(0.047)	(0.054)	(0.087)	(0.076)	(0.115)
low education	-0.243^{***}	-0.045	-0.015	0.036	0.014	-0.097	-0.105^{**}	-0.039
	(0.090)	(0.116)	(0.028)	(0.050)	(0.026)	(0.068)	(0.042)	(0.068)
high education	-0.123	0.017	0.015	0.144^{***}	-0.006	-0.232^{***}	-0.158^{**}	-0.109^{*}
	(0.113)	(0.128)	(0.033)	(0.039)	(0.027)	(0.089)	(0.070)	(0.057)
GDP per capita	-20.197^{***}	-10.037^{**}	-0.270	-1.750	0.144	2.219	-2.778	0.479
	(4.186)	(4.221)	(0.953)	(1.705)	(0.780)	(2.768)	(2.519)	(1.510)
import growth	0.016	0.004	0.009^{*}	-0.007	-0.005	0.027^{*}	0.029^{*}	0.009
	(0.033)	(0.013)	(0.006)	(0.007)	(0.003)	(0.015)	(0.016)	(0.011)
trade unions	-1.056^{***}	-0.165	0.042	0.058	-0.011	0.105	0.035	-0.062^{*}
	(0.162)	(0.109)	(0.031)	(0.040)	(0.022)	(0.071)	(0.057)	(0.034)
government exp.	0.178^{**}	0.023	-0.001	-0.007	0.00004	-0.074^{***}	-0.089^{***}	0.030
	(0.077)	(0.034)	(0.010)	(0.024)	(0.007)	(0.028)	(0.022)	(0.031)
observations	144	144	144	146	144	146	146	141
adjusted R^2	0.558	0.309	0.162	0.210	0.066	0.243	0.221	0.270

Notes: Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Source: Own estimation.

[3] This value was computed as follows: 9.871(standard deviation of *robot density*) × 0.421 (coefficient of *robot density*) = 4.2

In Table 3 we include the *ICT investment share*. The results of our main explanatory variable r*obot density* stay highly robust. However, the *ICT* variable has no effect on inequality. The *ICT investment shares* remain insignificant also if robotization is not included in the specification. Moreover, the signs often differ from the signs estimated for robotization, which indicates that the digitalization is not necessarily increasing inequality. The weak results may be due the specifics of digitalization process. For example, *ICT investment shares* remained relatively constant during the analyzed period, but the declining prices in this sector may imply their increasing importance. Alternatively, it may show that inequality increasing effects of new technologies are likely to disappear after sufficiently long transition periods.

3.4 Robustness Checks

We conduct two robustness checks. First, we estimate the impact of *robot density* on different measures of inequality for the years of the post financial crisis of 2007-2008. Therefore we exclude data before 2010. Table 4 shows that the effects regarding the post-crisis specification are robust to a limited extent. The direction of the effects remain the same as in the baseline model and five out of eight specifications show significant effects for our main explanatory variable *robot density*.

Second, we use sub-samples of core, as well as southern and northern European countries of the EU. The possible endogeneity channels are expected to be different for the analyzed subsamples. Thus, the stability of the results is important for the general validity of the main findings. For example, firms in relatively rich EU core countries as well as northern European countries are more likely to replace expansive labor by robots. Therefore, these countries may be more affected by the automation than relatively poor countries. However, the richer countries can have more financial means to deal with negative effects of robotization.

Tables 5 to 7 show the results for tree sub-samples, namely core, northern and southern European countries. The results are robust for the sub-sample of northern European countries. The polarization hypothesis can also be confirmed for the northern European countries. It is interesting to note that the northern European countries are more affected by automatization than the core countries. This shows that negative effects of robotization can be possibly counteracted by appropriate labor market policies, which were adopted in the core countries.

Table 4 The Impact of Robot Density on Different Measures of Inequality, Post Financial Crisis

	gini	*poverty risk*	*first quantile*	*bottom 50%*	*quantile ratio*	*top 10%*	*top 1%*	*130 median*
robot density	0.279**	0.215***	-0.069	-0.096**	0.049***	0.042	0.024	0.155***
	(0.130)	(0.083)	(0.083)	(0.043)	(0.012)	(0.060)	(0.059)	(0.049)
low education	-0.637***	-0.146	0.033	0.066	-0.026	0.038	-0.012	0.038
	(0.122)	(0.102)	(0.102)	(0.052)	(0.016)	(0.076)	(0.049)	(0.065)
high education	-0.152*	-0.025	0.029	0.056	-0.019**	0.011	0.035	-0.023
	(0.089)	(0.050)	(0.050)	(0.038)	(0.009)	(0.058)	(0.053)	(0.047)
GDP per capita	-22.813***	-19.838***	2.288	1.177	-2.116***	-0.176	-4.895	-5.339**
	(1.743)	(3.196)	(3.196)	(1.083)	(0.532)	(3.143)	(3.299)	(2.176)
import growth	0.030	-0.038	0.002	-0.023	0.0003	0.051*	0.041	-0.019
	(0.031)	(0.039)	(0.039)	(0.015)	(0.004)	(0.027)	(0.025)	(0.018)
trade unions	-0.466***	-0.214	0.062	-0.062	-0.061	-0.166*	-0.216***	-0.146*
	(0.085)	(0.140)	(0.140)	(0.059)	(0.041)	(0.096)	(0.069)	(0.077)
government exp.	0.110*	-0.058	-0.001	0.043***	0.004	-0.042	-0.044	-0.048*
	(0.065)	(0.047)	(0.047)	(0.014)	(0.006)	(0.036)	(0.033)	(0.029)
observations	81	81	81	81	81	81	81	78
adjusted R^2	0.646	0.392	0.041	0.083	0.145	0.174	0.204	-0.006

Notes: Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Source: Own estimation.

Table 3 The Impact of Robot Density on Different Measures of Inequality, Core Countries

	gini	*poverty risk*	*first quantile*	*bottom 50%*	*quantile ratio*	*top 10%*	*top 1%*	*130 median*
robot density	-0.118	0.069	-0.012	-0.161***	-0.004	0.200**	0.062*	0.144**
	(0.160)	(0.060)	(0.028)	(0.043)	(0.020)	(0.080)	(0.037)	(0.068)
low education	-0.160*	-0.108*	0.014	0.134***	0.0001	-0.094	-0.002	-0.102
	(0.091)	(0.063)	(0.028)	(0.035)	(0.015)	(0.080)	(0.043)	(0.171)
high education	-0.076	-0.086***	0.032**	0.160***	-0.018***	-0.193**	-0.071	-0.157**
	(0.097)	(0.019)	(0.013)	(0.043)	(0.006)	(0.098)	(0.063)	(0.072)
GDP per capita	2.488	-8.774***	-2.832***	1.370*	2.345***	1.965	0.601	0.814
	(3.775)	(2.299)	(0.641)	(0.706)	(0.310)	(1.523)	(0.656)	(4.477)
import growth	0.015	0.002	0.013**	-0.00001	-0.008**	-0.004	0.007	-0.012
	(0.033)	(0.008)	(0.006)	(0.014)	(0.003)	(0.024)	(0.012)	(0.020)
trade unions	-0.545***	-0.413***	-0.004	-0.004	0.021	0.247*	0.114	-0.125
	(0.162)	(0.091)	(0.073)	(0.054)	(0.042)	(0.134)	(0.097)	(0.165)
government exp.	-0.138*	-0.069	0.027	0.055	-0.010	-0.198***	-0.149***	-0.054
	(0.074)	(0.090)	(0.057)	(0.042)	(0.036)	(0.063)	(0.035)	(0.077)
observations	54	54	54	56	54	56	56	54
adjusted R^2	0.383	0.166	0.217	0.294	0.142	0.137	0.050	0.207

*Notes: Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Core countries are defined as Germany, France, Austria, Belgium, and the Netherlands.*

Source: Own estimation.

Table 6 The Impact of Robot Density on Different Measures of Inequality, Northern European Countries

	gini	*poverty risk*	*first quantile*	*bottom 50%*	*quantile ratio*	*top 10%*	*top 1%*	*130 median*
robot density	0.489***	0.067**	-0.011	-0.286***	0.026***	0.360***	0.287***	0.301***
	(0.160)	(0.031)	(0.011)	(0.057)	(0.004)	(0.097)	(0.085)	(0.069)
low education	0.252***	0.425***	-0.152***	0.234***	0.063***	-0.384***	-0.167*	-0.079
	(0.091)	(0.132)	(0.017)	(0.037)	(0.010)	(0.123)	(0.099)	(0.061)
high education	0.293***	0.773***	-0.112***	0.377***	0.033**	-0.744***	-0.413***	-0.102
	(0.097)	(0.212)	(0.023)	(0.077)	(0.014)	(0.135)	(0.115)	(0.104)
GDP per capita	-15.214***	-9.036***	-1.724***	-2.230	0.677***	5.465***	-0.509	1.219
	(3.775)	(3.173)	(0.298)	(2.744)	(0.145)	(1.435)	(1.469)	(2.005)
import growth	-0.025	0.009	0.023**	-0.009	-0.009*	0.073***	0.094***	0.015
	(0.033)	(0.008)	(0.010)	(0.023)	(0.006)	(0.020)	(0.006)	(0.015)
trade unions	-0.870***	0.110	-0.0001	0.135*	-0.003	-0.056	-0.033	-0.035
	(0.162)	(0.091)	(0.012)	(0.071)	(0.006)	(0.063)	(0.079)	(0.058)
government exp.	0.150**	-0.007	0.003	-0.039	0.0003	0.004	-0.028	0.020
	(0.074)	(0.036)	(0.004)	(0.028)	(0.003)	(0.020)	(0.017)	(0.027)
observations	51	51	51	51	51	51	51	50
adjusted R^2	0.621	0.424	0.492	0.505	0.494	0.533	0.580	0.482

Notes: Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Northern European countries are defined as Denmark, Sweden, Ireland, and Finland.

Source: Own estimation.

Table 7 The Impact of Robot Density on Different Measures of Inequality, Southern European Countries

	gini	*poverty risk*	*first quantile*	*bottom 50%*	*quantile ratio*	*top 10%*	*top 1%*	*130 median*
robot density	-0.073	-0.290	-0.062	0.106	0.056	0.158	0.195*	0.429**
	(0.160)	(0.368)	(0.124)	(0.092)	(0.117)	(0.162)	(0.109)	(0.190)
low education	0.025	0.336*	-0.155***	0.069	0.208***	0.013	-0.062	0.168*
	(0.091)	(0.202)	(0.044)	(0.069)	(0.043)	(0.109)	(0.054)	(0.101)
high education	0.983***	1.384***	-0.378***	-0.067	0.453***	0.093	-0.004	0.187
	(0.097)	(0.440)	(0.098)	(0.172)	(0.089)	(0.233)	(0.101)	(0.238)
GDP per capita	-24.036***	-14.242***	1.958*	1.253	-1.788	-2.636	-5.388*	-3.827*
	(3.775)	(4.742)	(1.082)	(1.729)	(1.123)	(4.000)	(3.158)	(2.059)
import growth	0.073**	0.031	-0.012***	-0.006	0.010**	-0.009	-0.014	0.012**
	(0.033)	(0.024)	(0.005)	(0.008)	(0.005)	(0.019)	(0.019)	(0.006)
trade unions	-0.509***	0.684***	-0.181***	-0.341***	0.180***	0.326***	-0.002	0.099
	(0.162)	(0.055)	(0.025)	(0.018)	(0.026)	(0.031)	(0.065)	(0.070)
government exp.	0.133*	-0.079**	0.044***	0.121***	-0.043***	-0.205***	-0.117**	-0.021
	(0.074)	(0.039)	(0.016)	(0.018)	(0.016)	(0.040)	(0.048)	(0.042)
observations	39	39	39	39	39	39	39	37
adjusted R^2	0.836	0.711	0.558	0.419	0.554	0.186	0.245	0.153

Notes: Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Southern European countries are defined as Spain, Italy, Portugal, and Greece.

Source: Own estimation.

4. Conclusions

Our model on the impact of *robot density* and share of *ICT investment* on a broad variety of inequality indicators provides additional evidence for earlier findings, which suggest that industrial robots are associated with rising income inequality. In comparison, the effect is not statistically significant for digitalization. In particular, we show that the income shares of the *bottom 20 percent* and *bottom 50 percent* decreases with automation, while the income shares of the *top 10 percent* and *top 1 percent* increases, which supports the job and wage polarization hypothesis.

The effects of *robot density* on different inequality measures are partly robust when excluding the financial crisis of 2007-2008, as well as for a subsample of core countries. The results of *robot density* are very robust for a subsample of northern European countries.

In the medium run, the rapid speed of technological advances, robots, and digital technologies will impact income distribution even more. For society to benefit from automation, a better and more nuanced understanding of the impact of robots and digital technologies on the labor maker is needed. Understanding how robotization and digitalization impact income inequality, can help to inform policymakers, NGOs, and employers, to advocate for policy-decisions to compensate the potential negative effect of technological changes. These issues are particularly important because we face a significant increase of digitalization and automation in nearly all areas of the labor market due to anti-pandemic measures. Future research could provide more comprehensive insights by including more countries with more diverse economies accounting for different automatization and digitalization dynamics.

APPENDIX

Table A1 Definition of Industrial Robots

ISO 8373:2012: “As an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place of mobile for use in industrial automation applications” (IFR, 2020).

In order to be included in the IFR database, the industrial robots must be in the production, imports, exports and installations/shipments sector and must meet following criteria:

- Reprogrammable: designed so that the programmed motions or auxiliary functions can be changed without physical alteration.
- Multipurpose: capable of being adapted to a different application with physical alteration.
- Ability for physical alteration (alteration of the mechanical system - the mechanical system does not include storage media, ROMs, etc.).
- Three or more axes (direction used to specify the robot motion in a linear or rotary mode)
- Fixed in place or mobile: The robot can be mounted at some other stationary point but it can also be mounted to a non-stationary point, e.g. railways (IFR, 2020).

Robots are included in the statistics based on their mechanical structure:

- Articulated robot: a robot whose arm has at least three rotary joints.
- Cartesian (linear/gantry) robot: robot whose arm has three prismatic joints and whose axes are correlated with a cartesian coordinate system.
- Cylindrical robot: a robot whose axes form a cylindrical coordinate system.
- Parallel/Delta robot: a robot whose arms have concurrent prismatic or rotary joints.
- SCARA robot: a robot, which has two parallel rotary joints to provide compliance in a plane.
- Others: Robots not covered by one of the above classes.

Equipment for loading/unloading of machine tools, assembly equipment, Integrated Circuit Handlers, automated storage and retrieval systems and guided vehicles or Autonomous Mobile Robots are not included in the statistic (IFR, 2020).

Table A2 Definition of Analyzed Variables

Variable	*Definition*	*Source*
gini coefficient	Gini coefficient of equivalized disposable income before social transfers	Eurostat (2020). https://ec.europa.eu/eurostat/de/data/database
poverty risk	People at risk of poverty or social exclusion in percentage of total population	Eurostat (2020). https://ec.europa.eu/eurostat/de/data/database
first quartile	Share of national equivalized income in the first quartile of income distribution in percentage of total population	Eurostat (2020). EU-SILC and ECHP survey https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=ilc_di01&lang=en
income shares:		
bottom 50%	National pre-tax income share held by bottom 50% income group	World Inequality Database (2020). https://wid.world/
top 10%	National pre-tax income share held by top 10% income group	
top 1%	National pre-tax income share held by top 1% income group	
130% median	Having income of 130% of median income or more in percentage of total population	Eurostat (2020). https://ec.europa.eu/eurostat/de/data/database
robot density	Stock of industrial robots per 10,000 employees	International Federation of Robotics https://ifr.org/
ICT Share	Share of ICT investment of computing equipment, communications equipment, computer software and databases by total assets	EU KLEMS (IT, CT and SOFT_DB) Capital https://euklems.eu/
education:		
low Educated	Percentage share active population with or less than lower secondary education	Eurostat (2020). https://ec.europa.eu/eurostat/de/data/database (Share of education attainment in active population from 15 to 74 years)
high Educated	Percentage share active population with at least tertiary education	
log GDP per capita	Log of Gross Domestic Product per capita	Eurostat (2020). https://ec.europa.eu/eurostat/de/data/database
import growth	Annual percentage growth in imports of goods and services	World Bank (2020), World Bank Database https://data.worldbank.org/
trade union	Trade union membership in workforce: Ratio of wage and salary earners that are trade union members, divided by the total number of wage and salary earners.	OECD (2020). https://data.oecd.org/
government exp.	Total general government expenditure as percent of GDP	Eurostat (2020). https://ec.europa.eu/eurostat/de/data/database

*Source: O*wn compilation. All data sets were retrieved in November 2020.

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