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by Costanza Bosone, Leonardo Gambacorta, Paolo Giudici, Enisse Kharroubi and Ulf Lewrick

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Robots, ICT and employment: evidence from advanced and emerging EU countries

Costanza Bosone, Leonardo Gambacorta, Paolo Giudici, Enisse Kharroubi and Ulf Lewrick*

Abstract

We study how robot adoption and investment in information and communication technologies (ICT) jointly shape sectoral employment across 20 European Union (EU) countries over the period 1995-2020. Using a cross-sectional regression design that interacts changes in robot adoption with ICT investment, we find that increases in robot adoption are associated with higher employment in sectors that either entered the period without robots or invested little in ICT. By contrast, robot adoption is associated with lower employment in sectors that initially had some robots and high ICT investment. These findings highlight the importance of both initial conditions and complementary technology investment in shaping labour-market outcomes, suggesting that the employment effects of technology are highly context-dependent.

Keywords: robotics, ICT capital, employment, labour market, technology adoption, European Union

JEL classification: E23, O33, J24

*Costanza Bosone is with the University of Pavia and Duke University. Paolo Giudici is with the University of Pavia. Leonardo Gambacorta, Enisse Kharroubi and Ulf Lewrick are with the Bank for International Settlements (BIS). The authors are thankful to Alexander Bridgwater for assistance with the data and to Iñaki Aldasoro, Jon Frost, Aaron Mehrotra and Tommaso Oliviero for helpful comments and suggestions. Disclaimer: The views expressed are those of the authors and do not necessarily reflect those of the BIS.

1 Introduction

Information and communication technologies (ICT) and industrial robotics have seen widespread adoption across sectors over the last few decades. This raises questions—and sometimes concerns—about their potential effects on firm labour demand and employment. In the short term, or in early adoption stages, these technologies may complement existing workers, boost productivity, and support job creation—especially in sectors where automation is still limited. ICT can enhance human capital by supporting cognitive-intensive tasks and enabling workers to focus on higher-value activities, while robotics may increase employment by raising output capacity and creating demand for complementary roles in supervision, maintenance, and integration. Under these conditions, technology adoption often goes hand in hand with rising labour demand, as firms require new technical, analytical, and operational skills to fully leverage digital tools and automation systems (Graetz and Michaels (2018); Ghodsi et al. (2020); Bessen (2020); Gaggl and Wright (2017)).

Over time, however, as these technologies mature, they may substitute for labour—especially in tasks that can be codified and automated—potentially reducing demand for certain occupations and skill groups (Acemoglu and Restrepo, 2020; de Vries et al., 2020; Hémous and Olsen, 2022). These dynamics are likely to intensify with the spread of generative artificial intelligence (genAI), which can automate not only routine tasks but also parts of non-routine cognitive work (Acemoglu et al., 2023; Brynjolfsson et al., 2023; Eloundou et al., 2023). Beyond their aggregate effects, the labour-market impact of these technologies crucially depends on how firms and sectors adjust their production processes, task allocation, and organisational structures in response to new technologies. Understanding this behavioural and organisational adjustment is essential to explain why similar technologies can generate sharply different employment outcomes across sectors and countries.

However, identifying the precise tipping point at which technology shifts from complementing labour to replacing it is a complex task. In particular, the timing and mechanics of this transition remain unclear. We seek to determine the factors that flip the relationship between technology investment and employment from positive (job creation) to negative (job displacement). To do so, we investigate how the proliferation of robotics and ICT investment has affected employment across sectors, considering both advanced and emerging countries from the European Union (EU) over the period 1995-2020. In this context, we exploit cross-sectoral variation in initial technology endowments across country-sector pairs to identify state-dependent effects.

Our main empirical results show that the relationship between employment and robot adoption depends critically on two factors: the sector's starting level of robotisation and its ICT investment. To illustrate how these two factors interact, consider a sector that started with no robots in 1995 but invested heavily in ICT over the subsequent period (with ICT investment at the top sample decile). In such a case, a one-standard-deviation increase in robotisation is then associated with an increase in annual employment growth of about 0.4 percentage points. This is roughly twice the effect estimated for comparable sectors with ICT investment in the bottom sample decile. For sectors that already possessed robots in 1995, a one-standard-deviation increase in robotisation leads to a 0.8 percentage point gain in employment growth when ICT investment is low (bottom sample decile), but to a decline of 0.4 percentage points when ICT investment is high (top sample decile). In highly automated or digitally advanced sectors, further increases in technology intensity therefore tend to depress employment growth, suggesting increasingly adverse employment effects as sectors climb the technology ladder.

Our paper contributes to the extensive literature studying the effects of automation and digital technologies, largely focused on the US labour market (e.g. Autor et al., 2003; Acemoglu and Restrepo, 2019; Graetz and Michaels, 2018; Ghodsi et al., 2020; Hémous and Olsen, 2022). We also contribute to the growing body of work examining the heterogeneous impact of technology across regions and countries (e.g. Gregory et al., 2016; Jestl, 2024; Park and Shin, 2025; Galassi and MacKenzie, 2026). While this literature documents heterogeneous effects of ICT and robotics mainly across sectors, our paper takes a different perspective by identifying state-dependent effects that emerge either because of differences in initial conditions— namely, baseline level of robot adoption—or from complementarities with other investments, in particular ICT.

The remainder of the paper is structured as follows. Section 2 describes the empirical strategy, including the sample, data sources, and econometric specifications. Section 3 presents the main results and a range of robustness checks. Section 4 concludes.

2 Empirical strategy

2.1 Sample and data

Our analysis draws on multiple data sources. Sectoral employment data come from Eurostat and are reported at the 2-digit level according to the NACE Rev. 2 classification (Nomenclature statistique des Activités économiques dans la Communauté Européenne). A detailed sectoral breakdown is provided in Appendix Table A. Data on industrial robots are sourced from the International Federation of Robotics (IFR), which compiles information on the stock of multi-purpose robots across manufacturing and non-manufacturing sectors.[1] These data are based on annual surveys conducted with robot suppliers. Due to data availability and the need to merge robot, ICT and employment data at the country–sector level, our final sample covers 20 EU countries over the period 1995–2020.

Turning to the variables of interest, we follow Aghion et al. (2019) and define "robotisation" as the change in robot adoption in sector s of country c between 1995 and 2020, denoted $\Delta\text{ROB}_{s,c}$:

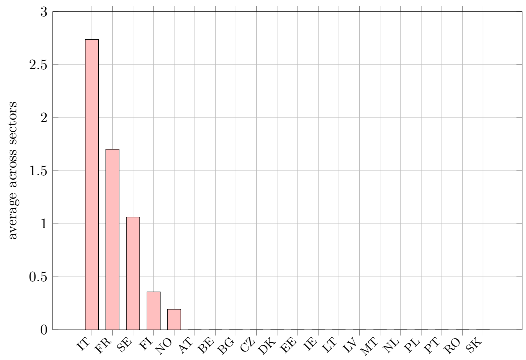
$$\Delta\text{ROB}_{s,c} = \frac{R^{20}_{s,c}}{L^{20}_{s,c}} - \frac{R^{95}_{s,c}}{L^{95}_{s,c}} \ , \tag{1}$$

where $R^t_{s,c}$ and $L^t_{s,c}$ are the number of robots and employment in sector s in country c in year t, respectively. Robotisation, $\Delta\text{ROB}_{s,c}$, therefore captures the extent to which sectors have increased their use of robots relative to their workforce.[2]

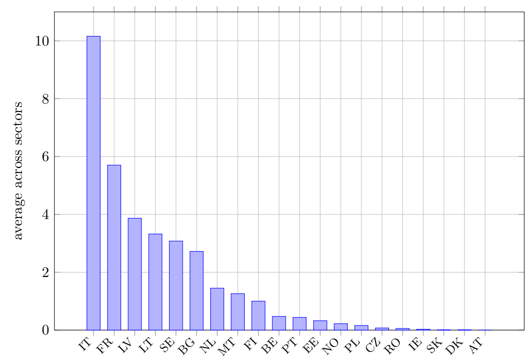
Figure 1a and **Figure 1b** show country averages for the initial level of robot exposure in 1995 and subsequent robotisation over the 1995-2020 period (as defined in expression (1)). Both panels reveal substantial cross-country heterogeneity. In many EU countries, especially in Central and Eastern Europe, robots were simply absent in 1995 (see Figure 1a). However, as **Figure 1b** shows, several countries (e.g. Latvia or Lithuania) made significant progress in robot adoption thereafter.

[1] According to the IFR, industrial robots are defined as automatically controlled, reprogrammable, multi-purpose manipulators programmable in three or more axes, used for industrial automation. This definition primarily captures articulated industrial robots and does not include other forms of automation such as autonomous vehicles, digitally controlled heavy machinery, or other sector-specific automated equipment.

[2] While expressing robotisation as the change in the ratio of robots to sectoral employment may hardwire a negative correlation between employment growth and robotisation, our empirical results are robust to this concern. In particular, using instead the change in the number of robots (without normalising with employment) leads to the same qualitative conclusions.



1a: Robots per 100 employees in 1995

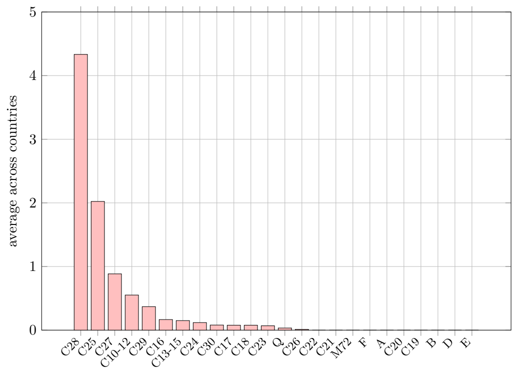


1b: Change in robots per 100 employees from 1995 to 2020

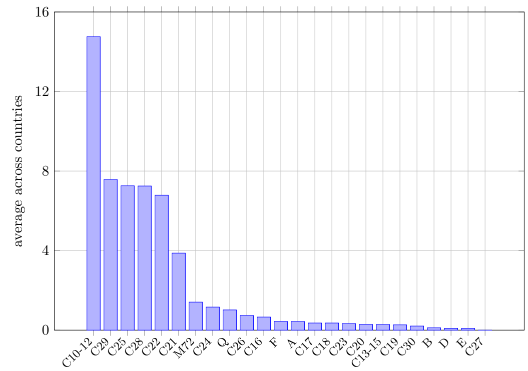
Figure 1: **Robots across countries.** Figure 1a plots the unweighted cross-sector average number of robots per 100 employees by country in 1995. Figure 1b reports the unweighted cross-sector average change in robots per 100 employees by country from 1995 to 2020. Country codes follow the ISO-2 classification.

At the same time, early adopters such as Italy, France and Sweden, which started with some of the highest stocks of robots in 1995, also recorded some of the largest increases over the subsequent 25 years. More broadly, the cross-country correlation between the level of robots in 1995 and the change in robot use over 1995-2020 is around 87%. This high correlation underscores a strong persistence phenomenon, whereby advanced markets increased their automation capabilities at a faster pace than others.

Figure 2 presents sectoral averages for robotisation, computed across countries. It shows that "Manufacture of machinery and equipment" (C28), "Manufacture of fabricated metal products" (C25) and "Manufacture of electrical equipment" (C27) had the highest number of robots per employee in 1995. By contrast, sectors such as "Mining and quarrying" (B) "Electricity, gas, steam and air conditioning supply" (D) or "Water supply, sewage, waste management and remediation" (E) did not use any robot in 1995. In addition, unlike the country averages, where initial levels and subsequent changes tend to be very strongly correlated, the cross-sectoral correlation between the level of robots in 1995 and the subsequent change in robot use is comparatively low, at about 45%. This difference with respect to **Figure 1** supports our empirical strategy: while countries may be locked into their automation patterns, sectoral adoption is far more dynamic, fluid and heterogeneous. For example the C22-sector ("Manufacture of rubber and plastic products") which had no robots in 1995, ranks fifth for the increase in the use of robots over 1995–2020. Conversely, the C27-sector (“Manufacture of electrical equipment”), which had one of the three highest ratios of robots per 100 employees in 1995 is the only sector for which the average change over 1995–2020 was (slightly) negative.



2a: robots per 100 employees
1995 level



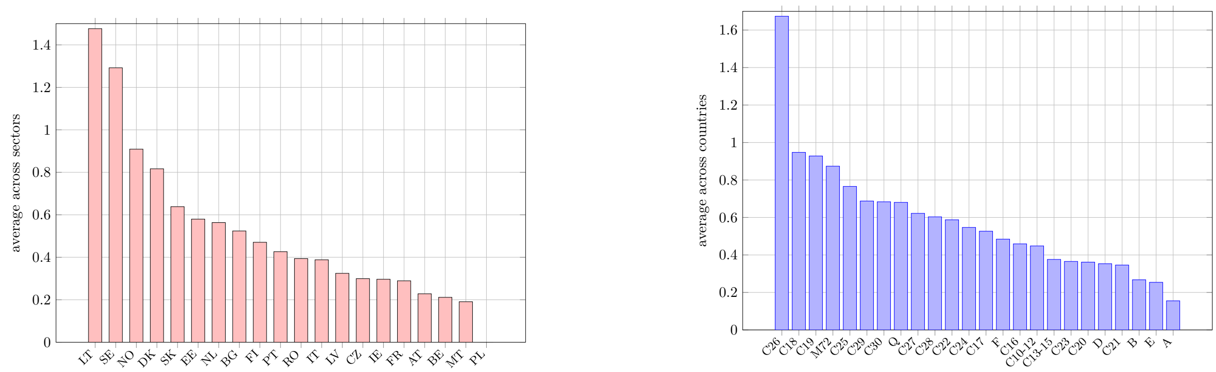
2b: Change in robots per 100 employees
from 1995 to 2020

Figure 2: **Robots across sectors.** Figure 2a plots the unweighted cross-country average number of robots per 100 employees by sector in 1995. Figure 2b shows the unweighted cross-country average change in the ratio of robots per 100 employees by sector between 1995 and 2020. Appendix Table A describes the sector codes used in Figure 2a and Figure 2b.

Next, we consider measures of ICT investment from the EU KLEMS Growth and Productivity Accounts. This data source provides stock and flow measures of capital inputs for EU Member States across 23 sectors over the period 1995–2020. It also records expenditures on information technology (IT) as well as on communication technology (CT). In contrast to the robot data, the ICT data follow the same industrial classification as the employment data (both based on NACE rev. 2), which enables a direct merge of the two datasets. We define ICT investment for sector s in country c between 1995 and 2020, denoted $\Delta\text{ICT}_{s,c}$, as the average ratio of nominal ICT investment expenditure to the one-year lagged nominal stock of fixed assets in sector s in country c.

$$\Delta\text{ICT}_{s,c} = \frac{1}{N_{s,c}} \sum_{t=1995}^{2020} \frac{ICT_{s,c,t}}{A_{s,c,t-1}} \tag{2}$$

where $ICT_{s,c,t}$ denotes ICT investments and $A_{s,c,t-1}$ the stock of fixed assets in sector s of country c in year $t-1$, while $N_{s,c}$ is the number of years between 1995 and 2020 for which both variables $ICT_{s,c,t}$ and $A_{s,c,t-1}$ are available.



3a: ICT by country
1995–2020 average

3b: ICT by sector
1995–2020 average

Figure 3: **ICT investment (1995–2020).** Figure 3a plots the unweighted cross-sector average ICT investment to fixed assets by country and Figure 3b presents the unweighted cross-country average ICT investment to fixed assets by sector.

Figure 3 displays differences in average ICT investment across countries and sectors over the period 1995–2020. It reveals substantial heterogeneity along both dimensions. At the country level, **Figure 3a** shows that several countries from Central and Eastern Europe, such as Lithuania, Slovakia or Estonia, rank among the highest ICT investors. By contrast, several countries from Western Europe, including France, Austria or Belgium, exhibit considerably lower ICT investment rates. Turning to sectors, **Figure 3b** indicates that "Manufacture of electrical equipment" (C26) and "Printing and reproduction of recorded media" (C18) are among the sectors with the largest ICT investments. At the opposite end of the spectrum are sectors where robot adoption remains negligible. This includes sectors such as "Agriculture, forestry and fishing" (A), "Water supply, sewage, waste management and remediation" (E) or "Mining and Quarrying" (B). Taken together, these figures highlight that robotisation and ICT are distinct phenomena driven by different forces: while robot adoption exhibits strong persistence at the country level, sectoral trends are more fluid, and ICT investment patterns suggest that emerging economies often outperform advanced economies.

2.2 Econometric specification

Our baseline specification estimates a relationship between the growth rate of employment or hours worked in sector s in country c, denoted $\Delta Y_{s,c}$—with Y representing the log of employment, E, or log of hours worked, H—and the change in robot adoption, $\Delta\text{Rob}_{s,c}$, as well as the change in ICT capital measured through ICT investment, $\Delta\text{ICT}_{s,c}$:

$$\Delta Y_{s,c} = \alpha_s + \alpha_c + \beta_i \cdot \Delta\text{ICT}_{s,c} + \beta_r \cdot \Delta\text{ROB}_{s,c} + \beta_x X_{s,c} + \varepsilon_{s,c} \tag{3}$$

Our empirical specification includes sector and country fixed effects, denoted by α_s and α_c, and a vector of control variables $X_{s,c}$, including: (i) the beginning-of-sample share of sectoral employment (or sectoral hours worked) in sector s in country c in total employment (or total hours worked); (ii) total imports and exports as a share of domestic value added, measured either in levels (in 1995) or as changes over the 1995-2020 period. Finally, we estimate specification (3) assuming heteroscedastic residuals $\varepsilon_{s,c}$.[3]

Next, in light of the large number of sectors that started without robots in 1995, we allow the coefficient on robot adoption, β_r, to differ between sectors that started with *some* robots (β_r^{nz}) and those that started with *none* (β_r^{z}). Our extended specification is given by:

$$\Delta Y_{s,c} = \alpha_s + \alpha_c + \beta_i \cdot \Delta\text{ICT}_{s,c} + \left[\beta_r^{nz} \cdot \mathbb{1}_{\boldsymbol{R^{95}_{s,c}>0}} + \beta_r^{z} \cdot \mathbb{1}_{\boldsymbol{R^{95}_{s,c}=0}}\right] \cdot \Delta\text{ROB}_{s,c} + \beta_x X_{s,c} + \varepsilon_{s,c} \tag{4}$$

where $\mathbb{1}_{\boldsymbol{X}} = 1$ if $\boldsymbol{X}$ is true and $\mathbb{1}_{\boldsymbol{X}} = 0$ otherwise. While the specific features of our sample motivate our choice to allow robot adoption to impact employment or hours worked differently for sectors with different initial levels of robots, there are also plausible economic mechanisms that may play out differently for sectors starting with some robots and those starting with none. In particular, introducing robots into sectors previously without any may actually require hiring additional workers, rather than shrinking the workforce, as existing workers may need retraining to become familiar with the new technologies. Conversely, expanding robot use in sectors that have already adopted some robots, and where workers are already familiar with new technologies, may more readily lead to employment cuts and substitution between labour and robots.

Finally, we extend our analysis by estimating the extent to which ICT investment may affect the impact of robotisation on employment. For this, we introduce an interaction term between

[3] In addition, we estimate specification (3) under different clustering assumptions, allowing either for clustering by country to control for shocks affecting all sectors within a given country, or clustering by sector to control for sectoral shocks that affect a given sector across all countries. Empirical results using these alternative clustering assumptions are qualitatively very similar and available from the authors upon request.

robot adoption and ICT investment, allowing the effect on employment (or hours worked) to differ across sectors that started with some robots and those that started with none:

$$\Delta Y_{s,c} = \alpha_s + \alpha_c + \beta_i \cdot \Delta \text{ICT}_{s,c} + \left[\beta_r^{nz} + \beta_{r/i}^{nz} \cdot \Delta \text{ICT}_{s,c}\right] \cdot \mathbb{1}_{\mathbf{R_{s,c}^{95}>0}} \times \Delta \text{ROB}_{s,c} + \\ + \left[\beta_r^{z} + \beta_{r/i}^{z} \cdot \Delta \text{ICT}_{s,c}\right] \cdot \mathbb{1}_{\mathbf{R_{s,c}^{95}=0}} \times \Delta \text{ROB}_{s,c} + \beta_x X_{s,c} + \varepsilon_{s,c}\,. \tag{5}$$

We estimate specifications (3), (4) and (5) using a cross-section of countries and sectors over the period 1995-2020. In addition, we also test the robustness of our results by considering alternative observation periods, specifically 2000–2020.[4]

Table 1 presents summary statistics of the main variables used in the regression analysis for the period 1995–2020. Over this time span, employment growth, while displaying substantial variation, has on average, been negative (about -13% over 25 years or -0.5% per year). This is unsurprising, as manufacturing sectors—which have been shrinking over time—are over-represented in our sample due to our focus on robots. In addition, sectoral employment growth appears very heterogeneous: employment in sectors at the 10^{th} percentile of the sample distribution shrank by about 90% between 1995 and 2020. Conversely, employment increased by about 50% in sectors at the 90^{th} percentile of the sample distribution.

By contrast, both robot adoption and ICT investment were, on average, positive over the period 1995–2020, although their distributions are highly skewed, indicating that both tend to be dominated by a small number of country-sector pairs (third and fourth columns in Table 1). For instance, ICT investment in sectors at the 90^{th} percentile of the sample distribution was about three and a half times greater than in sectors at the sample median. In the case of robot adoption, this ratio was much larger, about 20 times. Finally, the levels of robots in 1995 was zero for more than three out of four observations in our sample, indicating that a large fraction of the sectors in our sample started with no robots.

[4]Note that because our specifications test whether the relationship between robotisation and employment differs across sectors that started either with robots or without them, it is important for the sample period to start relatively early so as to cover both situations. If the sample had started later—for example in 2005 or 2010—the number of sectors without initial robot adoption would have been substantially smaller, making this empirical distinction considerably more difficult to implement.

Table 1: Summary Statistics

	Employment	**Hours worked**	**Robotisation**		**ICT investment**
	growth	growth	1995-level	change	average
Mean	−0.129	−0.197	0.338	2.004	0.550
SD	0.551	0.555	2.232	6.951	1.006
$\mathbf{p_{10}}$	−0.878	−0.893	0.000	0.000	0.035
$\mathbf{p_{25}}$	−0.425	−0.502	0.000	0.020	0.133
$\mathbf{p_{50}}$	−0.120	−0.148	0.000	0.180	0.333
$\mathbf{p_{75}}$	0.222	0.155	0.000	0.860	0.611
$\mathbf{p_{90}}$	0.534	0.489	0.150	3.750	1.143
Skew.	−0.264	−0.426	10.64	8.004	9.455
Kurt.	3.907	3.959	131.8	89.03	123.6
Obser.	301	301	301	301	301

Notes: Table 1 shows summary statistics for the main variables of interest. Employment growth is the log-difference of sectoral employment between 1995 and 2020. Robotisation level (change) refers to the level of (the change in) the ratio of robots per 100 employees, in 1995 (between 1995 and 2020). Average ICT investment refers to the ratio of ICT investment to the stock of fixed assets, averaged between 1995 and 2020. **SD** is the standard deviation, $\mathbf{p_n}$ is the n-th percentile, **Skew.** is the skewness, and **Kurt.** is the kurtosis.

3 Results

Table 2 summarises our main empirical results and is organised into two parts. The first part, covering columns (1) to (4), examines the relationship between sectoral employment growth on the one hand and robotisation and ICT investment on the other hand. The second part of Table 2 from columns (5) to (8) explores this relationship by considering growth in hours worked instead of growth in employment.

Table 2 reveals important patterns in the correlations between key variables. First, as would be expected, both employment growth and growth in hours worked correlate negatively with their respective initial levels (first and second row). In addition, both dependent variables correlate positively with ICT investment, and the estimated coefficients remain stable across specifications (third row). In contrast, robotisation—when introduced linearly in the regression—carries a positive but insignificant coefficient, suggesting that it does not have a significant correlation with either employment or hours worked (fourth row). This finding would be consistent with the view that the unconditional impact of robots on employment would be negligible.

Table 2: Robotisation, ICT Investment and Employment Growth (1995–2020)

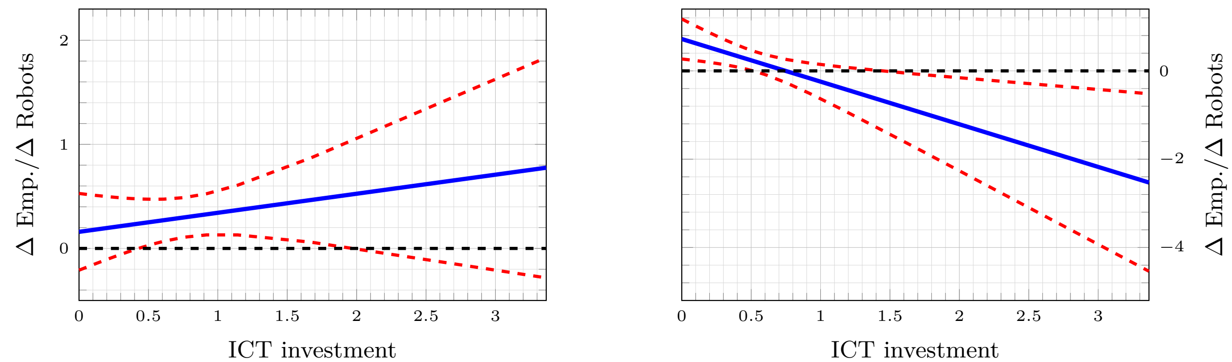
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**Employment growth**				**Growth in hours worked**			
Initial employment	-0.212^{a}	-0.210^{a}	-0.220^{a}	-0.216^{a}				
	(0.048)	(0.048)	(0.048)	(0.048)				
Initial hours worked					-0.194^{a}	-0.191^{a}	-0.201^{a}	-0.195^{a}
					(0.065)	(0.065)	(0.065)	(0.066)
ICT investment	0.065^{a}	0.070^{a}	0.068^{a}	0.064^{a}	0.060^{a}	0.066^{b}	0.063^{a}	0.059^{b}
	(0.022)	(0.025)	(0.022)	(0.025)	(0.022)	(0.025)	(0.023)	(0.025)
Robotisation	0.611	0.960			0.641	1.035		
	(0.373)	(0.739)			(0.401)	(0.804)		
ICT investment × **Robotisation**		−0.631				−0.728		
		(1.140)				(1.320)		
Robotisation, initial robots = 0			1.680^{c}	0.974			1.924^{c}	1.118
			(0.880)	(1.364)			(1.006)	(1.479)
ICT investment × **Robotisation**, initial robot = 0				1.117				1.244
				(1.492)				(1.690)
Robotisation, initial robots > 0			0.349^{c}	1.254^{a}			0.360^{c}	1.326^{a}
			(0.209)	(0.477)			(0.215)	(0.504)
ICT investment × **Robotisation**, initial robot > 0				-1.677^{b}				-1.809^{b}
				(0.748)				(0.828)
Observations	301	301	301	301	276	276	276	276
R-squared	0.612	0.613	0.617	0.620	0.595	0.596	0.602	0.607

Notes: The dependent variable **employment growth** (**growth in hours worked**) is computed over the period 1995-2020. **Initial employment** (**hours worked**) is measured as the log-level of sectoral employment (hours worked) in 1995. **ICT investment** refers to the ratio of ICT investment to fixed assets, averaged over 1995-2020. **Robotisation** is defined as the change between 1995 and 2020 in the ratio of robots per employee. Initial robots=0 (Initial robots>0) is a binary variable equal to one for sectors whose level of robots per employee in 1995 was zero (strictly positive), and zero otherwise.Superscripts [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are robust to general heteroscedasticity. Country and sector fixed effects are included in the regressions but omitted from the table.

Columns (2) and (6) introduce an interaction term between ICT investment and robotisation. In both cases, this term has a negative coefficient estimate, although it is not statistically significant. This implies that while robotisation may have a positive impact on employment, this benefit tends to shrink in sectors with higher average ICT investment. Conversely, it suggests that the positive impact of ICT investment on employment is weaker in sectors where robotisation is more prevalent. That said, given the lack of statistical significance for the interaction term, any potential dampening effect of ICT investment or robotisation is unlikely to be economically meaningful.

Rows (6) to (8) refine the analysis of possible interactions between ICT investment and robotisation by allowing coefficients for sectors that already used some robots in 1995 to differ from those (the vast majority in the sample) that had none at the outset of our sample. This differentiation allows the estimated coefficients to vary between these groups, offering greater insight into sectoral heterogeneity. The results, presented in columns (3)-(4) and (7)-(8), show that this separation leads to significant changes. Specifically, robotisation correlates positively and significantly with employment growth in both columns (3) and (7). In addition, the coefficient for sectors that started with no robots in 1995 is about five times larger than the coefficient for sectors that started with some robots in 1995, suggesting that increasing the number of robots is associated with higher employment growth when robots constitute a new technology. In contrast, for sectors where robots were already in use, the relationship between robots and employment is significant but much weaker. Furthermore, columns (4) and (8) show that ICT investment (robotisation) tends to meaningfully offset the impact of robotisation (ICT investment) on employment, but only in sectors that were already using robots in 1995. For sectors without robots in 1995, the interaction between robotisation and ICT investment is positive but not statistically significant, indicating that both robotisation and ICT investment are associated with higher employment, albeit with weaker statistical significance in the case of robotisation.

The conclusions from Table 2 are therefore twofold. First, in sectors that start from scratch, i.e. with no robots in 1995, employment increases with ICT investments and robotisation. In these sectors, which are arguably in the first steps of integrating new technologies, robotisation and ICT investment are not associated with job losses; by contrast, the introduction of new technologies tends to be associated with more dynamic employment. Second, in sectors already using robots in 1995, employment still increases with ICT investments, but only when robotisation remains limited. Similarly, employment still rises with robotisation, but only when ICT investments are modest. However, when robotisation is substantial, employment tends to fall with ICT investments and similarly, when ICT investments are large, employment falls with further robotisation. These results suggest that the employment effects of technology are state-dependent. In sectors already highly automated, modest increases in robots or ICT remain complementary to labour, but large simultaneous investments tend to generate substitution effects and weaker employment outcomes.



4a: Sectors without robots in 1995

4b: Sectors using some robots in 1995

Figure 4: **The impact of robotisation on employment for sectors *without* or *with* robots in 1995.** The blue line in each panel plots the estimated percentage change in annual sectoral employment growth resulting from a one-standard-deviation increase in the change in the ratio of robots to 100 employees, conditional on ICT investment over 1995-2020. The left-hand (right-hand) panel plots the estimated change in the growth rate of employment for sectors that initially started with no (some) robots. Dashed red lines in each panel indicate the 90% confidence interval around the mean estimate. For example, when ICT investment averages 2% of fixed assets, annual employment growth increases by about 0.6 percentage points (decreases by about 1.4 percentage points) for a one-standard-deviation increase in the change in robots per employee in sectors that started without robots (with some robots).

To provide a sense of the magnitudes involved, we illustrate the impact of a one-standard-deviation increase in robotisation on yearly employment growth for different levels of ICT investment, distinguishing between sectors without robots (**Figure 4a**) and those with robots (**Figure 4b**) in 1995. For sectors starting without robots, the employment boost is positive across the distribution, but scales with ICT intensity. In low-ICT environments (10^{th} percentile), a standard shock to robotisation raises annual employment growth by less than 0.2 percentage points. This effect doubles to 0.4 percentage points in high-ICT environments (90^{th} percentile). Conversely, for sectors already using robots (**Figure 4b**), the outcome depends entirely on the ICT context. In low-ICT sectors (10^{th} percentile), robotisation drives a robust employment gain of 0.8 percentage points per year. However, in high-ICT sectors (90^{th} percentile), the relationship flips, resulting in an annual employment decline of 0.4 percentage points. Crucially, **Figure 4b** reveals the precise tipping points: robotisation correlates positively with employment when ICT investment is below 0.5% of fixed assets (covering about two-thirds of the sample), but turns statistically negative once ICT investment exceeds 1.4%—a high-intensity threshold reached by only 5% of observations.

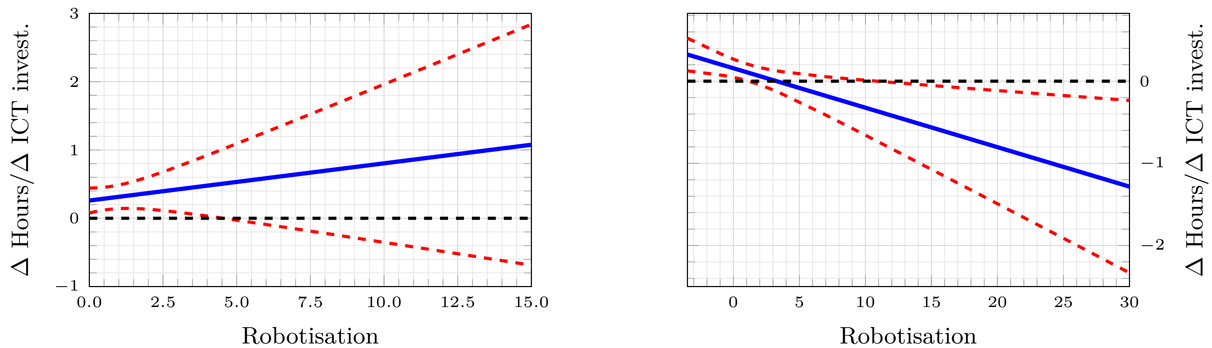
Figure A in the Appendix provides a graphical representation of the relationship between robotisation and growth in hours worked, based on the regression results in column (8) of Table 2. By focusing on hours worked, this analysis allows us to examine adjustments along both the intensive and extensive margins of labour input. Distinguishing between employment growth and hours worked therefore allows us to separate labour-market adjustments operating through the extensive margin (changes in the number of workers) which would correspond to changes in the size of firms or sectors, from those operating through the intensive margin (changes in hours per worker), which relate to the internal organisation of firms. This distinction could indeed be particularly relevant in the context of technological adoption, where firms may initially respond by adjusting working time before changing employment levels.

Consistent with our previous findings, the impact of robotisation on hours worked depends strongly on ICT investment and on whether sectors were already using robots or introduced them for the first time. Importantly, the patterns observed in **Figure A** closely mirror those reported in **Figure 4** for employment growth. This similarity suggests that the employment effects of robotisation documented in the paper primarily reflect adjustments in the number of workers, rather than changes in hours worked per employee. In other words, the main effects of robotisation appear to operate primarily through changes in the employment base (the extensive margin), rather than through internal adjustments in working time, such as overtime (the intensive margin).

It is useful at this stage to examine how hours worked respond to changes in ICT investment, conditional on the level of robotisation.[5] **Figure 5** illustrates this relationship by distinguishing between the two cases analysed previously: sectors that did not use robots in 1995 (**Figure 5a**) and sectors that already employed some robots at the beginning of the sample period (**Figure 5b**). The two horizontal axes highlight a marked difference in the scope of robot adoption across these groups. In particular, the range of robotisation—measured as the change in robots per 100 employees—is about two times wider for sectors that started with robots (−3.5 to +30.0) compared to those that did not (0.0 to +15.0).

[5]**Figure B** in the Appendix provides a graphical representation of the impact of ICT investment on employment for sectors without and using some robots. The results are very similar to those reported in **Figure 5**.

Figure 5a focuses on sectors without robots in 1995. In the absence of robot adoption, a one-standard-deviation increase in ICT investment raises growth in hours worked by about 0.25 percentage points per year. This positive effect approximately doubles—to 0.5 percentage points—in sectors that added around five robots per 100 employees, indicating a strong complementarity between ICT investment and the introduction of robotics when automation is still at an early stage.



5a: Sectors without robots in 1995

5b: Sectors using some robots in 1995

Figure 5: **The impact of ICT investment on hours worked for sectors *without* and *using some* robots in 1995.** The blue line in each panel plots the estimated percentage change in annual sectoral growth in hours worked, resulting from a one standard deviation increase in ICT investment, as a ratio of fixed assets, conditional on the increase in robots per 100 employees over 1995-2020. The left-hand (right-hand) panel plots the estimated change in the growth of hours worked for the case of sectors without (using some) robots in 1995. Dashed red lines plot in each panel the 90% confidence interval around the mean estimate.

Figure 5b considers sectors that already employed robots in 1995. When robot use remains broadly unchanged, ICT investment increases hours worked by about 0.15 to 0.2 percentage points annually—an effect slightly lower but overall comparable to that observed in sectors that initially had no robots. However, this relationship reverses as robot adoption intensifies. In sectors adding 10 robots per 100 employees, ICT investment is associated with a decline in hours worked of around 0.35 percentage points. This negative effect becomes stronger at higher levels of robotisation: at the 90th percentile of robot adoption, a one-standard-deviation increase in ICT investment leads to a reduction in the yearly growth rate of hours worked of approximately 0.65 percentage points, which roughly corresponds to one-quarter of the sample's standard deviation of growth in hours worked.

Robustness checks. To assess the robustness of our main empirical results, we repeat the regressions presented in Table 2 over a shorter period, from 2000 to 2020. The results, detailed in Table 3, suggest that shortening the period of observation does not affect our conclusions. In particular, employment in sectors without robots in 1995 continues to grow at a faster pace when these sectors invest more in ICT or increase their use of robots, although the latter correlation is only marginally significant. In addition, the interaction between ICT investment and robotisation remains positive, suggesting that higher investment in one enhances the employment growth benefit of higher investment in the other.

Table 3: Robotisation, ICT Investment and Employment Growth (2000–2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**Employment growth**				**Growth in hours worked**			
Initial employment	-0.190^{a}	-0.188^{a}	-0.197^{a}	-0.191^{a}				
	(0.044)	(0.044)	(0.044)	(0.044)				
Initial hours worked					-0.162^{a}	-0.160^{a}	-0.169^{a}	-0.164^{a}
					(0.056)	(0.056)	(0.056)	(0.057)
ICT investment	0.046^{a}	0.053^{b}	0.048^{a}	0.047^{b}	0.042^{b}	0.049^{b}	0.044^{b}	0.043^{c}
	(0.018)	(0.022)	(0.018)	(0.021)	(0.018)	(0.023)	(0.018)	(0.022)
Robotisation	0.480^{c}	0.978			0.570*	1.069		
	(0.288)	(0.907)			(0.333)	(1.023)		
ICT investment × **Robotisation**		−0.975				−0.988		
		(1.657)				(1.925)		
Robotisation, initial robots = 0			1.242	0.940			1.629^{c}	1.247
			(0.753)	(1.232)			(0.861)	(1.366)
ICT investment × **Robotisation**, initial robot = 0				0.377				0.497
				(1.592)				(1.813)
Robotisation, initial robots > 0			0.269	1.936^{b}			0.306^{c}	1.860^{b}
			(0.164)	(0.779)			(0.171)	(0.900)
ICT investment × **Robotisation**, initial robot > 0				-3.240^{b}				-3.043^{c}
				(1.495)				(1.738)
Observations	301	301	301	301	282	282	282	282
R-squared	0.546	0.547	0.550	0.554	0.542	0.543	0.549	0.552

Notes: The dependent variable **Employment growth** (**Growth in hours worked**) is computed over the period 2000-2020. **Initial Employment** (**hours worked**) is the log-level of sectoral employment (hours worked) in 2000. **ICT investment** refers to the ratio of ICT investment to fixed assets, averaged over 2000–2020. **Robotisation** is the change between 2000 and 2020 in the ratio of robots per 100 employees. Initial robots=0 (Initial robots>0) is a dummy variable that is equal to one for sectors whose level of robots per 100 employees in 2000 was zero (was strictly positive). Superscripts [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are robust to general forms of heteroscedasticity. Country and sector fixed effects are included in the regressions but omitted from the table. The reported R-squared includes country and sector dummies.

As found for the larger sample, in sectors already using some robots in 2000, increased robot adoption is associated with higher employment, but this holds only when ICT investment is low. When robot adoption occurs alongside high ICT investment, the correlation becomes negative and employment falls in response to greater use of robots.

Finally, in addition to testing our results over alternative time periods, we also consider potential confounding factors that may affect both technology investments (ICT and robots) and labour market outcomes (employment and hours worked), thereby generating possibly spurious correlations. Specifically, openness to international trade is a relevant example as it could lead firms to both automate their production processes and increase the use of ICT and robots, while simultaneously reducing employment to lower labour costs and better withstand competition from firms in low-income countries. We address this possibility by including an additional control for trade openness, measured as the ratio of total imports and exports to domestic value added, either in 1995 levels (see Appendix Table B) or in changes over the 1995-2020 period (see Appendix Table C). In addition, we also estimate the extended specification using the change in this ratio over the 2000-2020 period (see Appendix Table D).

This analysis provides three main empirical results. First, the initial level of trade openness typically carries a positive but insignificant coefficient (third row in Appendix Table B) while barely affecting our main results. In particular, employment growth and robotisation are still positively related in sectors that started with no robots. In sectors that had some robots to start with, the correlation turns from positive to negative as ICT investment gets larger. Second, Appendix Table C shows that employment growth correlates negatively with the increase in openness to trade (third row). Sectors where imports and exports grew faster than domestic value added also had significantly lower employment growth over the same period. That said, this negative correlation does not affect our main empirical results: the relationship between robotisation and employment growth is still positive in sectors that had no robots in 1995 but negative in those that had some robots in 1995 and made large investments in ICT. Last, estimating the extended specification—with the change in openness to trade—over the 2000-2020 period brings virtually no change. In particular, the negative relationship between employment growth and changes in trade openness remains robust, while our main conclusions regarding the relationship between robotisation, ICT investment and labour outcomes, both for employment and hours worked, continue to hold.

4 Conclusion

This paper examines the joint effects of ICT investment and industrial robot adoption on sectoral growth in employment and hours worked across EU countries over the period 1995–2020. The results show that the labour market implications of technology adoption are highly heterogeneous and depend crucially on both initial conditions and the interaction between different forms of technology investments.

In sectors with negligible prior automation—as captured by an inexistent stock of robots, both robot adoption and ICT investment are associated with higher employment growth and higher growth in hours worked. In these contexts, new technologies appear to complement labour, likely reflecting adjustment and integration processes that require additional skills and organisational adaptation. Empirical evidence also suggests some form of complementarity between robot adoption and ICT investment, whereby increases in one amplify the positive employment effects of the other.

By contrast, in sectors with an established presence of robots, the relationship between technology and labour market outcomes turns out to be non-linear. While moderate increases in robot adoption or ICT investment continue to be associated with positive employment outcomes, higher speed of technology adoption is linked to lower—and in some cases negative—growth in employment or hours worked. In particular, employment growth tends to fall in response to robot adoption when the latter occurs alongside substantial ICT investment, pointing to diminishing returns and potential crowding-out effects as automation deepens.

Taken together, these findings highlight the importance of sectoral adjustment dynamics and organisational context in shaping labour-market responses to technological change. They suggest that the labour market implications of automation cannot be characterised by single average relationships alone, but instead reflect state-dependent responses that vary across sectors and stages of technological adoption. From a policy perspective, these results imply that support measures may need to be differentiated across sectors, with particular attention to highly automated environments where further technological investment may be more likely to displace labour. As digital and automation technologies continue to advance, understanding these state-dependent effects — and the implications of alternative policy responses — becomes increasingly important.

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Appendix: Supplementary material

Table A: Sector classification based on NACE Rev. 2

Code	**Description**
A	Agriculture, forestry, fishing
B	Mining and quarrying
C10–C12	Manufacture of food products; beverages and tobacco products
C13–C15	Manufacture of textiles, wearing apparel, leather and related products
C16	Manufacture of wood and of products of wood and cork, except furniture
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
D	Electricity, gas, steam and air conditioning supply
E	Water supply, sewerage, waste management and remediation activities
F	Construction
M72	Scientific research and development
Q	Human health and social work activities

Table B: Robots, ICT Investment and Employment Growth (1995–2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	1995-2020 Employment growth				1995-2020 Growth in hours worked			
Initial employment	-0.174^{a}	-0.171^{a}	-0.183^{a}	-0.178^{a}				
	(0.058)	(0.058)	(0.058)	(0.058)				
Initial hours worked					-0.147^{b}	-0.144*	-0.155^{b}	-0.149^{b}
					(0.074)	(0.075)	(0.075)	(0.075)
Initial imports and exports	0.491	0.476	0.416	0.342	0.315	0.298	0.220	0.146
	(0.602)	(0.600)	(0.595)	(0.598)	(0.635)	(0.632)	(0.626)	(0.632)
ICT investment	0.047	0.052	0.052	0.051	0.050	0.056	0.057	0.056
	(0.038)	(0.039)	(0.037)	(0.038)	(0.039)	(0.040)	(0.038)	(0.039)
Robotisation	0.577	0.913			0.623	1.015		
	(0.364)	(0.747)			(0.391)	(0.803)		
ICT investment × **Robotisation**		−0.611				−0.722		
		(1.192)				(1.320)		
Robotisation, initial robots = 0			1.587^{c}	0.839			1.843^{c}	1.053
			(0.920)	(1.380)			(1.013)	(1.490)
ICT investment × **Robotisation**, initial robot = 0				1.180				1.215
				(1.568)				(1.710)
Robotisation, initial robots > 0			0.348^{c}	1.267^{a}			0.365^{c}	1.346^{a}
			(0.210)	(0.485)			(0.213)	(0.510)
ICT investment × **Robotisation**, initial robot > 0				-1.719^{b}				-1.844^{b}
				(0.783)				(0.854)
Observations	263	263	263	263	248	248	248	248
R-squared	0.596	0.597	0.601	0.605	0.581	0.582	0.587	0.593

Notes: The dependent variable **Employment growth** (**Growth in hours worked**) is computed over the period 1995-2020. **Initial Employment** (**hours worked**) is the log-level of sectoral employment (hours worked) in 1995. **Initial imports and exports** is the ratio in 1995 of imports and exports to value added. **ICT investment** refers to the ratio of ICT investment to fixed assets, averaged over 1995–2020. **Robotisation** is the change between 2000 and 2020 in the ratio of robots per 100 employees. Initial robots=0 (Initial robots>0) is a dummy variable that is equal to one for sectors whose level of robots per 100 employees in 1995 was zero (was strictly positive). Superscripts [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are robust to general forms of heteroscedasticity. Country and sector fixed effects are included in the regressions but omitted from the table. The reported R-squared includes country and sector dummies.

Table C: Robots, ICT Investment and Employment Growth (1995–2020)

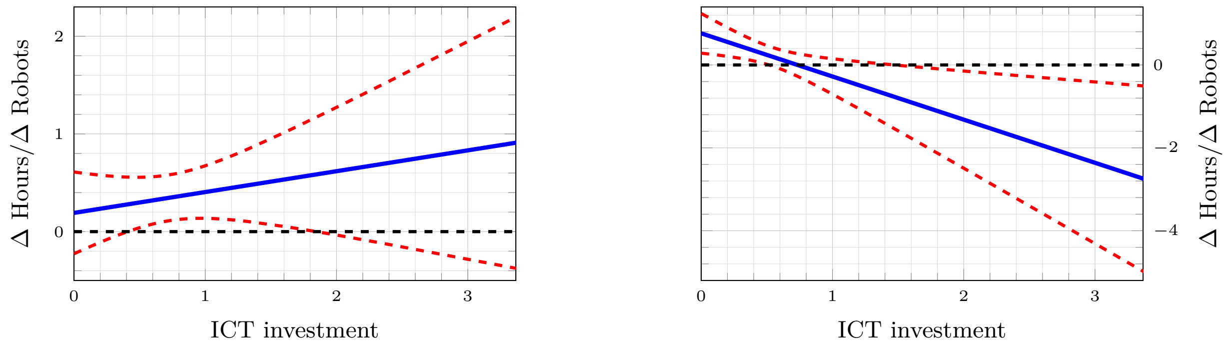
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	1995-2020 Employment growth				1995-2020 Growth in hours worked			
Initial employment	-0.219^{a}	-0.216^{a}	-0.229^{a}	-0.223^{a}				
	(0.055)	(0.055)	(0.055)	(0.055)				
Initial hours worked					-0.219^{a}	-0.216^{a}	-0.227^{a}	-0.220^{a}
					(0.066)	(0.066)	(0.065)	(0.066)
Change in imports and exports	-0.330^{a}	-0.330^{a}	-0.333^{a}	-0.328^{a}	-0.425^{a}	-0.426^{a}	-0.425^{a}	-0.420^{a}
	(0.122)	(0.123)	(0.118)	(0.118)	(0.117)	(0.118)	(0.113)	(0.113)
ICT investment	0.066^{a}	0.071^{a}	0.068^{a}	0.065^{a}	0.060^{a}	0.066^{a}	0.063^{a}	0.061^{a}
	(0.020)	(0.023)	(0.020)	(0.023)	(0.019)	(0.022)	(0.020)	(0.022)
Robotisation	0.660^{c}	1.024			0.693^{c}	1.120		
	(0.387)	(0.734)			(0.409)	(0.765)		
ICT investment × **Robotisation**		−0.664				−0.787		
		(1.129)				(1.213)		
Robotisation, initial robots = 0			1.758^{c}	1.121			1.930^{b}	1.314
			(0.893)	(1.364)			(0.956)	(1.428)
ICT investment × **Robotisation**, initial robot = 0				0.971				0.891
				(1.506)				(1.595)
Robotisation, initial robots > 0			0.409^{c}	1.255^{a}			0.429^{c}	1.313^{a}
			(0.220)	(0.461)			(0.227)	(0.487)
ICT investment × **Robotisation**, initial robot > 0				-1.581^{b}				-1.657^{b}
				(0.677)				(0.748)
Observations	263	263	263	263	248	248	248	248
R-squared	0.632	0.632	0.637	0.641	0.642	0.643	0.649	0.653

Notes: The dependent variable **Employment growth** (**Growth in hours worked**) is computed over the period 1995-2020. **Initial Employment** (**hours worked**) is the log-level of sectoral employment (hours worked) in 1995. **Change in imports and exports** is the change between 1995 and 2020 in the ratio of imports and exports to value added. **ICT investment** refers to the ratio of ICT investment to fixed assets, averaged over 1995–2020. **Robotisation** is the change between 2000 and 2020 in the ratio of robots per 100 employees. Initial robots=0 (Initial robots>0) is a dummy variable that is equal to one for sectors whose level of robots per 100 employees in 1995 was zero (was strictly positive). Superscripts [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are robust to general forms of heteroscedasticity. Country and sector fixed effects are included in the regressions but omitted from the table. The reported R-squared includes country and sector dummies.

Table D: Robots, ICT Investment and Employment Growth (2000–2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	2000-2020 Employment growth				2000-2020 Growth in hours worked			
Initial employment	-0.185^{a}	-0.182^{a}	-0.194^{a}	-0.186^{a}				
	(0.048)	(0.048)	(0.048)	(0.048)				
Initial hours worked					-0.170^{a}	-0.166^{a}	-0.177^{a}	-0.170^{a}
					(0.052)	(0.052)	(0.051)	(0.052)
Change in imports and exports	-0.312^{a}	-0.314^{a}	-0.314^{a}	-0.311^{a}	-0.392^{a}	-0.394^{a}	-0.393^{a}	-0.391^{a}
	(0.093)	(0.094)	(0.091)	(0.091)	(0.085)	(0.087)	(0.082)	(0.084)
ICT investment	0.053^{a}	0.061^{a}	0.054^{a}	0.055^{a}	0.050^{a}	0.060^{a}	0.052^{a}	0.054^{b}
	(0.018)	(0.022)	(0.018)	(0.021)	(0.017)	(0.022)	(0.017)	(0.021)
Robotisation	0.524^{c}	1.138			0.593^{c}	1.287		
	(0.305)	(0.930)			(0.336)	(0.984)		
ICT investment × **Robotisation**		−1.206				−1.370		
		(1.715)				(1.843)		
Robotisation, initial robots = 0			1.371^{c}	1.156			1.635^{b}	1.477
			(0.782)	(1.272)			(0.826)	(1.345)
ICT investment × **Robotisation**, initial robot = 0				0.134				−0.018
				(1.665)				(1.768)
Robotisation, initial robots > 0			0.303^{c}	1.995^{a}			0.337^{c}	1.963^{b}
			(0.172)	(0.762)			(0.176)	(0.821)
ICT investment × **Robotisation**, initial robot > 0				-3.296^{b}				-3.172^{b}
				(1.443)				(1.554)
Observations	266	266	266	266	256	256	256	256
R-squared	0.576	0.578	0.581	0.585	0.607	0.609	0.614	0.618

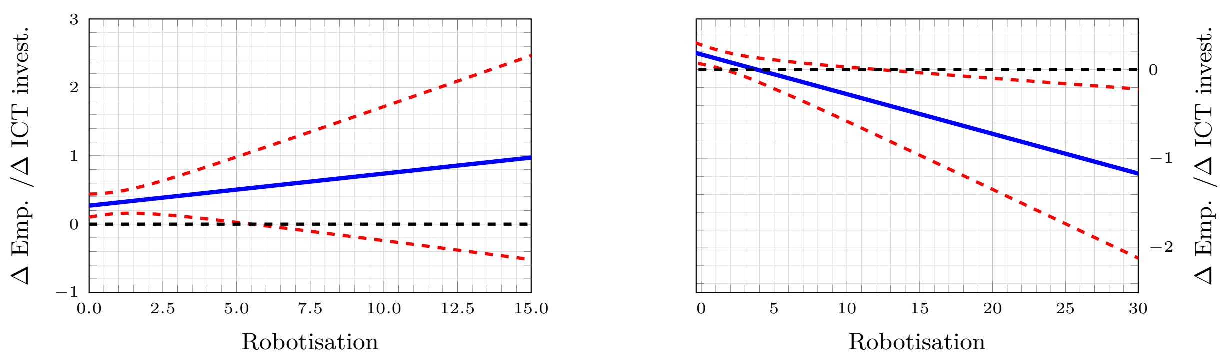
Notes: The dependent variable **Employment growth** (**Growth in hours worked**) is computed over the period 2000-2020. **Initial Employment** (**hours worked**) is the log-level of sectoral employment (hours worked) in 2000. **Change in imports and exports** is the change between 2000 and 2020 in the ratio of imports and exports to value added. **ICT investment** refers to the ratio of ICT investment to fixed assets, averaged over 2000–2020. **Robotisation** is the change between 2000 and 2020 in the ratio of robots per 100 employees. Initial robots=0 (Initial robots>0) is a dummy variable that is equal to one for sectors whose level of robots per 100 employees in 2000 was zero (was strictly positive). Superscripts ^{a}, ^{b}, and ^{c} denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are robust to general forms of heteroscedasticity. Country and sector fixed effects are included in the regressions but omitted from the table. The reported R-squared includes country and sector dummies.



A1: Sectors without robots in 1995

A2: Sectors using some robots in 1995

Figure A: **The impact of robotisation on hours worked for sectors *without* and *using some* robots in 1995.** The blue line in each panel plots the estimated percentage change in annual sectoral growth in hours worked, resulting from a one standard deviation increase in the change robots per 100 employees, conditional on ICT investment, as a ratio of fixed assets. The left-hand (right-hand) panel plots the estimated change in the growth of hours worked for the case of sectors without (using some) robots in 1995. Dashed red lines plot in each panel the 90% confidence interval around the mean estimate.



B1: Sectors without robots in 1995

B2: Sectors using some robots in 1995

Figure B: **The impact of ICT investment on employment for sectors *without* and *using some* robots in 1995.** The blue line in each panel plots the estimated percentage change in annual sectoral growth in employment, resulting from a one standard deviation increase in ICT investment, as a ratio of fixed assets, conditional on the change in robots per 100 employees. The left-hand (right-hand) panel plots the estimated change in the growth of employment for the case of sectors without (using some) robots in 1995. Dashed red lines plot in each panel the 90% confidence interval around the mean estimate.

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