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Artificial Intelligence, Robots and Unemployment: Evidence from OECD Countries

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ABSTRACT

Investigating the relation between artificial intelligence, robots and unemployment on a panel of 33 OECD countries covering the 2005—2017 period, we find that a 10% increase in the stock of industrial robots is associated with a 0.42 point increase in the unemployment rate. For artificial intelligence (AI), we use patents as a proxy of AI-related technological capabilities and find a positive correlation with the aggregated unemployment rate, albeit statistically weaker than the one found for robots. We then run the regressions on unemployment rates differentiated by education and age, and observe highly heterogeneous effects between groups. For example, the effect of robots is 2.5 times greater for 25-34 year-olds below upper secondary education levels than for the 55-64 year-olds with a tertiary degree. Lastly, the effect of robots is strongest on the unemployment rate of people with a medium level of education, providing some evidence that robots could contribute to the polarization of the labor market. A similar effect is found with AI, but the results are less robust than for robots.

KEYWORDS: Technological Unemployment, Skill-biased Technical Change, Labor Market Polarization, Robots, Artificial Intelligence, Robotics, Okun's Law

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The resurgence of the concept of technological unemployment both in the labor economics literature and in the media highlights fears that technical progress could be job-destructive. This anxiety is rooted in the view that exponential technical progress will lead to a relentlessly growing automation of production.

Two relatively recent branches of computer sciences have come to fuel this vision: robotics and AI. The first is a continuation of the previous technological revolutions that have taken place in history, and aims to lighten the drudgery of work, to push back the frontier of technology while improving the efficiency of production. From the ancient Roman cranes that built aqueducts to the modern cranes that build ever taller skyscrapers, from the invention of printing (attributed to Gutenberg in the mid-15th century, despite evidence that Tang Dynasty China (618—907) had already mastered printing techniques by the 8th century (Gunaratne, 2001), to modern printing presses that have contributed to accelerating the diffusion of information by speeding up printing while decreasing costs, from manual looms replaced by the spinning jenny in the middle of the 18th century to modern looms that increase the quantity produced tenfold, all these inventions have made human work less arduous, more productive and increased the quality of manufactured products. Robotics is part of this continuity, allowing a drastic reduction of the amount of human work per unit of capital, by automating the operation of machines.

Artificial intelligence is also in line with the search for efficiency, but differs from the previous innovations in that it does not automate manual tasks, but cognitive tasks. In this sense, it is part of the continuity of the digital revolution with the rise of computer science, making it possible to perform computational tasks easily and quickly. What is new with artificial intelligence (AI) lies in its adaptive characteristics, compared to traditional algorithms, which are static. The difference could be formulated as follows: a traditional algorithm is programmed to perform a task; a machine learning algorithm is programmed to learn to perform a task. When the degree of complexity of a task is low, the first approach is much more efficient and consumes less time and resources. However, when the degree of complexity increases, the second method is much more powerful and sometimes leads to a result that was not anticipated by the developers. This type of algorithm is particularly effective for problems requiring tacit knowledge, which is, by definition, difficult to codify. For example, machine learning techniques have greatly accelerated the development of autonomous cars. Driving is a simple task, but it requires a great capacity of adaptation that was very difficult to implement with traditional algorithms that would have required anticipating all possible scenarios that the car could have faced.

The objective of this paper is to answer a very simple question: is there empirical evidence that robotics and AI technologies could increase unemployment? We want to reason at the macro level because what matters to us here is the net effect of job destruction and creation, *i.e.*, testing the effectiveness of compensating mechanisms. Calvino and Virgillito (2018) distinguished between two types of compensation mechanisms: classical and Keynesian-Schumpetarian. The former encompasses four different mechanisms: an increase in labor demand in the firms producing the process innovations, a drop in prices due to productivity gains that then leads to an increase in aggregate demand, a decrease in wages that in turn increases labor demand, and an increase in investment financed by the decrease in the unitary cost of production generated by process innovation, thus triggering new hiring to expand production. The second category includes two mechanisms: an increase in wages due to productivity gains for the workers remaining in the firm, thus boosting consumption; and the creation of new products that open new markets and thus increase labor demand.

The paper is structured as follows: we will present the literature review on the link between robotization, AI and unemployment, we will then develop our research hypotheses, then we will present the methodology and data we used to answer them, the following section will be devoted to the analysis of the results and we will conclude in the final section.

Literature Review

Opinions on technological unemployment are divided between pessimistic and optimistic views. This last position was shared by Keynes (1930), who called for a decrease in working time to avoid technological unemployment: "*Three-hour shifts or a fifteen-hour week may put off the problem for a great while*" (Keynes, 1930, p. 5). Rifkin (1995) went even further by predicting the end of work, depicting an almost fully automated economy that would produce an abundant quantity of goods and services at a marginal cost of close to zero (Rifkin, 2014).

The evidence on technological unemployment in the growing body of research on the effects of technical progress is mixed. When looking at how many jobs could be potentially automated in the next two decades, the literature provides estimates as high as 47% (Frey, Osborne, 2017) to as low as 9% for the US (Arntz *et al.*, 2016). Nedelkoska and Quintini (2018) used data from the PIAAC database covering 32 OECD countries and found that about 14% of jobs are highly automatable. Using the automation risk measure developed by these authors, Georgieff and Milanez (2021) analyze whether or

not jobs considered at a high risk of automation in 2012 actually experienced a net loss of workers seven years later. They found that these occupations saw a weaker employment growth than other jobs, and even sometimes a modest decline in employment levels. However, the authors point out that, at the aggregate level, automation does not result in net job destruction. Felten *et al.* (2019) proposed an "AI Occupational Impact" measure and found that, while artificial intelligence has a small positive effect on wages, it has no impact on employment. Acemoglu *et al.* (2020) used data on online vacancies and found no correlation between AI exposure and employment and wages. This conclusion is not shared by Webb (2019), who found that jobs with high exposure to automation technologies experienced a decline in employment and wages. Building on Frey and Osborne (2017) and Felten *et al.* (2018), Fossen and Sorgner (2019) found that a high computerization risk is associated with an increasing likelihood of changing occupation or being unemployed.

At the firm level, Bessen *et al.* (2019) investigated the relation between automation and jobs and concluded that automation increases workers' likelihood of leaving the firm. However, they note that this effect is gradual and small in magnitude. Koch *et al.* (2021) conducted an analysis on a panel of Spanish manufacturing firms and pointed out that robot adoption led to a net increase in jobs of 10%, while firms that did not invest in robots suffered job losses over the period. Aghion *et al.* (2020) used French data and found that automation has a positive impact on employment, both at the firm and industry level. Montobbio *et al.* (2022) matched labor-saving robotics patents with firm-level data, and highlighted a sector-specific effect on manual and cognitive tasks. In addition to studies on robotics and artificial intelligence, an entire body of literature addresses the effects of process innovations on employment. Van Roy *et al.* (2015) found that process innovation tends to increase employment, whereas other studies observed no evidence of a meaningful relation between the two (Harrisson *et al.*, 2014; Calvino, 2019; Barbieri *et al.*, 2019).

While analysis at the firm level has the advantage of offering a large amount of data, often of better quality than macroeconomic data, it has the disadvantage of not providing a practical framework for answering the question of the net effect of technological progress on employment at the aggregate level. Indeed, some job losses in one firm or sector can potentially be offset by the creation of new jobs in other firms or sectors.

Meso-level and macro-level analysis allow for bypassing the limitations of firm-level studies. Dauth *et al.* (2018) looked at the effects of robot adoption on the German labor market, and found that it has changed the job distribution across industries without decreasing the aggregate level of employment. Graetz and Michaels (2018) used sectoral data on a panel of seventeen

countries and found no significant reduction in total employment. They did, however, point out that increased robotization is associated with a decrease in the employment share of low-skilled workers. Acemoglu and Restrepo (2020) used a task-based theoretical framework to analyze the effect of robot density on local labor markets in the US, and found that one additional robot per thousand workers is associated with a drop of 0.2 percent in the employment-to-population ratio and a decrease in wages of 0.37 percent. They also emphasized the heterogeneity of the effects by showing that the lower the workers' level of education, the stronger the negative impact on jobs and hourly wages. Chiacchio *et al.* (2018) employed a similar methodology across six European Union countries and estimated a negative impact of 0.16 to 0.20 points on the employment-to-population ratio. They found a particularly strong displacement effect for young males with a medium level of education. Autor and Salomons (2018) turned their attention to the effects of robotization on the labor share and concluded that automation has contributed to its decline since the 1980s.

Research Hypotheses

Based on the empirical and theoretical literature, we formulate four research hypotheses. First, we expect to observe a positive correlation between the aggregate unemployment rate, robots and AI (H1). While some authors (Graetz, Michaels, 2018; Chiacchio *et al.*, 2018; Acemoglu, Restrepo, 2020) have highlighted a negative (positive) impact on employment (unemployment), the quantitative effect of AI on jobs at the macro level is currently not well covered. Second, we expect a positive correlation between robots and the unemployment rate of the least educated workers, and a negative correlation between robots and the unemployment rate of those with a high level of education (H2). This hypothesis is consistent with the skill-biased technical change (SBTC) theory: unskilled workers are negatively impacted by technological progress while skilled workers benefit from it. Conversely, we test the hypothesis that AI and robots mainly have an impact on the unemployment rate of medium-skilled workers (H3). This is in reference to the literature on labor market polarization (Autor *et al.*, 2006) for the US, Salvatori (2018) for the UK, Furukawa and Toyoda (2018) for Japan, Goos *et al.* (2014) for Europe, according to which AI algorithms mainly substitute for routine tasks performed by medium-skilled workers.

Finally, we expect heterogeneous effects within a same education group and between age classes. Two opposing effects could come into play: an "experience" effect and a "knowledge obsolescence" effect. The first effect

is due to the fact that older workers tend to have more work experience and are therefore, at a similar education level, are more qualified. As a result, the tasks performed by older workers should be more complex than those of younger workers, and thus they should be less exposed to technological unemployment. The second effect postulates that young people tend to be more technologically savvy than seniors. For example, 25-34 year-olds tend to be more comfortable with computer and mobile technologies than their 55-64 year-olds counterparts with a similar level of education. This effect particularly makes sense for the most educated workers, who are most likely to be employed as data scientists, software developers, robot engineers, etc.

While we expect the former effect to prevail for the less educated, we expect the latter to prevail for the more educated. As a result, we expect a positive correlation between robots and the unemployment rate of young people with a low education level (and a negative or not significant effect on the unemployment rate of older people with the same education), and a negative correlation between AI and the unemployment rate of young people with a high education level (and a positive or not significant effect on the unemployment rate of seniors with the same level of education) (H4).

Methodology and Data

To test these four hypotheses, we study the relationship between AI, robots and unemployment rates. This approach allows us to observe the net effects of compensation mechanisms at the macro level, and not just the impacts in specific firms or industries. Our dataset consists of a panel of 33 OECD countries[1] and covers the 2005—2017 period, except for Iceland (2009—2016), Ireland[2] (2005—2014) and Israel (2007—2017). We use unemployment rates that we regress on GDP growth which, as has been known since Okun (1963), explains a significant part of the variation in the unemployment rate (*U*); on the inactivity rate (*IR*), which can have a direct impact on unemployment by increasing or decreasing the labor force, and on the growth rate of the robots (*IR*) and AI patent stocks (*AI*). The choice of taking the first difference instead of the levels is motivated by the non-stationarity of the data, as illustrated in Figures 1 and 2. To account for potential lags between the

1. Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Korea, Latvia, Lithuania, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United States.
2. Ireland's GDP grew by 26% in 2015, which is mostly the statistical result of multinational companies relocating their intellectual property for fiscal reasons. For Israel, data related to the unemployment rates by level of education are not available for 2006.

variation of our robots and AI variables and the effect on unemployment, we also include the growth rate of t-1 and t-2 for these two variables. Given that unemployment can sometimes keep increasing even as its causes have faded (known as the "hysteresis effect"), we also include a lag of the dependent variable. Formally, we estimate the following specification:

$$U_{ijt}^{k} = \alpha + \beta_1 U_{ijt-1}^{k} + \beta_{2,3} \ln Y_{jt-m} + \beta_{4,5} IR_{ijt-m}^{k} + \beta_{6,7,8} Robots_{jt-\boldsymbol{n}} + \beta_{9,10,11} AI_{jt-n} + \varepsilon_{ijt}^{k} \quad (1)$$

Where U_{ijt}^{k} is the unemployment rate of education group *i* of age class *k* in country *j* at time *t*, *Y* is the real GDP per capita expressed in dollar purchasing power parity, *IR* is the inactivity rate, *Robots* the growth rate of the stock of industrial robots and *AI* the growth rate of the stock of patents related to artificial intelligence. m ∈ {0, 1} and n ∈ {0, 1, 2} define the lags for *Y* and *Robots/AI* variables respectively.

Data on real GDP per capita and unemployment rates are provided by the OECD. Unemployment and inactivity rates are collected from the labor force surveys conducted by the national statistical offices and centralized by the OECD. The different levels of educational attainment correspond to the 2011 International Standard Classification of Education (ISCED) elaborated by UNESCO. The OECD (2017) uses the ISCED levels 0 to 2 for the category "below upper secondary education", 3 to 4 for the category "upper secondary or post-secondary non-tertiary education" and 5 to 8 for the category "Tertiary education". For each education category, we have four age groups: 25-34, 35-44, 45-54, and 55-64 year-olds.

Data on the operational stock of robots were obtained from the International Federation of Robotics (IFR). The IFR provides macro data starting from 1993 to 2017 for most countries. However, changes in methodology in 2004—2005 led to an underestimation of the operational stock for some countries. To avoid any major bias and to ensure methodological consistency in our sample, we chose to begin our analysis in 2005. An important limitation of the IFR database is that for the period covered, data on service robots[3] are not available. Therefore, when we use the term "robots", we refer to industrial robots defined by the IFR as "*an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications*" (IFR, 2016, p. 25). Figure 1 shows the evolution of the average robot density in our sample. The 2005—2017 period follows an upward trend.

3. IFR (2018) provides the following definition for service robots: "*a robot that performs useful tasks for humans or equipment excluding industrial automation applications*".

Figure 1 – Evolution of the average stock of robots

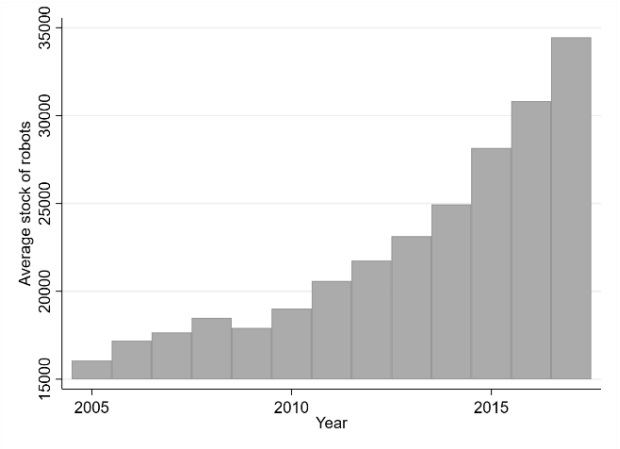
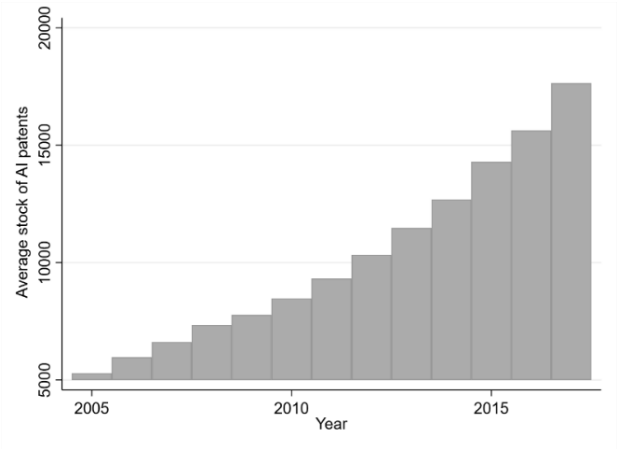


Figure 2 – Evolution of the average stock of AI patents



Lastly, we identified patents related to AI using a methodology developed by the World International Patent Office (WIPO, 2019). The approach is based on a combination of keywords and IPC / CPC codes. We then computed the patent stock by using the perpetual inventory method. We start in 1956, the date of Dartmouth conference organized by John McCarthy, considered as the event that formalized AI as a new field of study and research (Warwich, 2012). Figure 2 retraces the evolution of the average AI patent stock, which follows a similar trend to that of robots. Conceptually, we use patents as a proxy for technological capabilities, that is, the ability to select,

acquire, generate and apply technologies. What we are trying to estimate is the relationship between the growth of AI-related technological capabilities and the unemployment rate. The faster these capabilities evolve, the more the organizational structures and production processes of firms could be disrupted, which would impact the unemployment rates through quantitative and qualitative human resources adjustments.

Some concerns could be raised regarding the use of patents as a proxy for progress in AI-related technological capabilities. First, this approach does not allow us to capture unpatented innovations, and is therefore sensitive to changes in patenting behavior (Öcalan-Özel, Pénin, 2016). However, the surge in the number of patents since 2013 is consistent with the exponential number of scientific publications in the field (WIPO, 2019), and does not seem to be driven by a massive change in the patenting strategy of the firms. Second, one may ask whether these technologies have had time to spread through the economy. Some surveys indicate that AI technologies are already implemented in an increasing number of firms. McKinsey (2018) conducted a survey of over 2000 American firms over 10 industries, and found that 47% of these companies have embedded at least one AI capability into their business processes. Gartner (2019) gathered data on over 3000 chief information officers over 89 countries, and found that 37% of firms had already deployed AI technologies in their operations or were planning to do so in the near future.

An alternative measure would have consisted in using R&D expenditure instead of patents, but this proxy has several limitations: to the best of our knowledge, there is no macroeconomic data on R&D expenditure devoted to artificial intelligence; and R&D expenditure is a measure of inputs to the innovation process, not outputs such as patents. The best measure would have been data on the capital stock related to AI. The national accounts provide data on the capital stock of software and databases, but it is impossible to distinguish which part is AI-related. For this reason, patents, while not fully satisfactory, are currently the best available indicator and are regularly used in the literature (Lacour, Figuière, 2014).

Results

First, we estimate equation (1) with a fixed effect model. The results are presented in Table 1. However, the estimator for dynamic panels may be biased (Nickell, 1981). To overcome this bias, we re-estimate the model with the GMM system estimator (Blundell, Bond, 1998). The results are presented in Table 2. For each GMM regression, we compute the Hansen test for overidentification restrictions.

The results are presented in Table 1 and 2. The dependent variable $U_{i=0}^{k=25-64}$ represents the unemployment rate of the 25-64 year-olds, $U_{i=1}^{k=25-64}$ for the unemployment rate of the 25-64 year-olds with a below upper secondary education level, $U_{i=2}^{k=25-64}$of the 25-64 year-olds for the unemployed with upper secondary or post-secondary non-tertiary education levels and $U_{i=3}^{k=25-64}$ of the 25-64 year-olds for the unemployed with a tertiary education level. Since the fixed effect estimator could be biased, we will only comment on the results obtained with GMM. Considering the aggregate unemployment rate ($U_{i=0}^{k=25-64}$) in Table 1, we find Okun's law through the negative correlation between real GDP growth per capita and the unemployment rate. Robots seem to have an impact on the unemployment rate, and the second lag of the AI variable does appear to be positively correlated (a 1% increase in the AI patent stock in t-2 is associated with an increase of 0.027 points in the unemployment rate in t). This temporal difference could be explained by the measurement methods of these two variables: while the "robots" variable reflects the stock of industrial robots used in the production process, the "AI" variable reflects the stock of patents related to artificial intelligence. While the former variable reflects productive capacities, the second is a shortcut for technological progress in the field of artificial intelligence, and there is a lag between the discovery of a new technology and its use in production.

Examining the unemployment rates by education level provides some interesting insights. First, we note that the absolute value of Okun's coefficient is inversely correlated to the level of education: the unemployment rate of those with a below upper secondary education level ($U_{i=1}^{k=25-64}$) is 2.7 time more sensitive to the economic conjuncture than the unemployment rate of those with a tertiary degree ($U_{i=3}^{k=25-64}$). Second, we note that the effect of AI on unemployment is concentrated on $U_{i=1}^{k=25-64}$ and $U_{i=2}^{k=25-64}$, while no significant correlation is found for the most educated part of the labor force $U_{i=3}^{k=25-64}$. Third, we observe that robots are positively correlated with unemployment rates, for each education category. When we compute the net effect over a three-year period, we find that $U_{i=1}^{k=25-64}$ and $U_{i=2}^{k=25-64}$ are more affected than $U_{i=3}^{k=25-64}$, with the strongest effect on $U_{i=2}^{k=25-64}$.

To test the fourth research hypothesis, we estimate equation (1) with unemployment rates differentiated by both education level and age group. The results of the GMM estimates are presented in Tables 3, 4 and 5; and results for the fixed effect estimates are presented in Tables A1, A2 and A3 in the appendix. A first observation is that while some effects are shared across age groups, other effects identified in Tables 1 and 2 are concentrated in only one or two age groups. For example, the negative correlation between $AI(t)$ and $U_{i=1}^{k=25-64}$ observed in Table 1 is found in three of the four age groups presented in Table 4; and we observe a similar pattern for the positive correlation

between *Robots*(*t*) and $U_{i=2}^{k=25-64}$ (Table 3). In contrast, the positive correlation between *Robots*(*t*) and $U_{i=1}^{k=25-64}$ highlighted in Table 1 appears to come only from the 25-34 year-olds (Table 3). Second, the variation in the magnitude of the coefficients shows than there is significant heterogeneity in the effects within the same education category but across different age groups. For example, the correlation coefficient between *Robots*(*t*) and $U_{i=2}^{45-54}$ is almost twice as high as that between the same variable and $U_{i=2}^{25-34}$. This gap is, however, partially filled by the presence of compensation mechanisms that are illustrated by a negative correlation with the lagged values of the *Robots* variable, but this effect is present only for the 35-44 and 45-54 age groups.

Table 1 – **Panel estimates $U_{i=0}^{k=25-64}$—and $U_{i=1}^{k=25-64}$**

	$U_{i=0}^{k=25-64}$		$U_{i=1}^{k=25-64}$	
	FE	GMM-SYS	FE	GMM-SYS
$U_i^k(t-1)$	0.216***	0.102	0.177*	0.066
	(0.064)	(0.095)	(0.088)	(0.078)
$Y(t)$	-0.312***	-0.341***	-0.469***	-0.496**
	(0.039)	(0.073)	(0.075)	(0.066)
$Y(t-1)$	-0.096**	-0.147***	-0.192***	-0.270***
	(0.039)	(0.035)	(0.050)	(0.053)
$IR_i^k(t)$	-0.059	-0.072	0.112	0.017
	(0.117)	(0.143)	(0.091)	(0.170)
$IR_i^k(t-1)$	-0.186	-0.255*	0.104	0.139
	(0.114)	(0.135)	(0.089)	(0.126)
$AI(t)$	-0.012	-0.019	-0.062	-0.186***
	(0.016)	(0.017)	(0.050)	(0.054)
$AI(t-1)$	-0.007	-0.014	0.028	0.050
	(0.015)	(0.012)	(0.028)	(0.039)
$AI(t-2)$	0.024**	0.027***	0.020	0.049**
	(0.011)	(0.009)	(0.024)	(0.023)
Robots(t)	0.010	0.042***	0.015**	0.035**
	(0.003)	(0.009)	(0.006)	(0.017)
Robots$(t-1)$	-0.003	-0.007	0.007	-0.000
	(0.003)	(0.010)	(0.010)	(0.017)
Robots$(t-2)$	-0.001	-0.009	0.012*	0.012
	(0.006)	(0.006)	(0.006)	(0.012)
Intercept	0.127	0.185	0.178	1.283
	(0.408)	(0.424)	(0.725)	(0.999)
Time dummies	Yes	Yes	Yes	Yes
Observations	319	319	319	319
R^2	0.7228		0.6435	
AR(1)		0.000		0.000
AR(2)		0.690		0.222
Hansen		0.505		0.203

Notes: Robust standard errors in parenthesis, clustered at country-level.
** p < 0.10 ** p < 0.05 *** p < 0.01*

Table 2 – **Panel estimates — $U_{i=2}^{k=25-64}$ and $U_{i=3}^{k=25-64}$**

	$U_{i=2}^{k=25-64}$		$U_{i=3}^{k=25-64}$	
	FE	GMM-SYS	FE	GMM-SYS
$U_i^k(t-1)$	0.136*	0.041	0.102	0.145*
	(0.071)	(0.090)	(0.092)	(0.081)
$Y(t)$	-0.374***	-0.418***	-0.174***	-0.182***
	(0.042)	(0.081)	(0.032)	(0.056)
$Y(t-1)$	-0.134***	-0.201***	-0.094***	-0.112***
	(0.047)	(0.043)	(0.026)	(0.024)
$IR_i^k(t)$	-0.056	-0.101	0.059	0.145*
	(0.101)	(0.140)	(0.092)	(0.081)
$IR_i^k(t-1)$	-0.244*	-0.322**	-0.001	-0.009
	(0.131)	(0.142)	(0.052)	(0.069)
$AI(t)$	-0.018	-0.042	0.004	0.015
	(0.022)	(0.029)	(0.010)	(0.021)
$AI(t-1)$	-0.020	-0.033	-0.004	-0.014
	(0.018)	(0.020)	(0.011)	(0.015)
$AI(t-2)$	0.028*	0.028*	-0.002	-0.005
	(0.014)	(0.015)	(0.010)	(0.015)
$Robots(t)$	0.014***	0.056**	0.006	0.026***
	(0.004)	(0.011)	(0.003)	(0.009)
$Robots(t-1)$	-0.008**	-0.017	0.004	0.004
	(0.004)	(0.012)	(0.004)	(0.008)
$Robots(t-2)$	-0.004	-0.015**	-0.000	-0.004
	(0.008)	(0.007)	(0.003)	(0.006)
Intercept	0.535	0.951	0.111	0.118
	(0.477)	(0.685)	(0.251)	(0.419)
Time dummies	Yes	Yes	Yes	Yes
Observations	319	319	319	319
R^2	0.6688		0.5729	
AR(1)		0.000		0.003
AR(2)		0.763		0.841
Hansen		0.247		0.135

Notes: Robust standard errors in parenthesis, clustered at country-level.
** p < 0.10 ** p < 0.05 *** p < 0.01*

Table 3 – $U_{i=1}$ differentiated by age group - GMM-SYS estimates

	$U_{i=1}^{k=25-34}$	$U_{i=1}^{k=35-44}$	$U_{i=1}^{k=45-54}$	$U_{i=1}^{k=55-64}$
$U_i^k(t-1)$	-0.313***	-0.344***	-0.088	-0.231**
	(0.098)	(0.063)	(0.142)	(0.115)
$Y(t)$	-0.499***	-0.520***	-0.665***	-0.313**
	(0.158)	(0.138)	(0.142)	(0.115)
$Y(t-1)$	-0.639***	-0.402***	-0.253***	-0.252***
	(0.115)	(0.043)	(0.080)	(0.046)
$IR_i^k(t)$	0.018	-0.032	0.131	0.077
	(0.108)	(0.140)	(0.081)	(0.099)
$IR_i^k(t-1)$	-0.006	0.029	-0.004	0.083
	(0.150)	(0.073)	(0.098)	(0.093)
$AI(t)$	-0.245***	-0.127**	-0.073	-0.210**
	(0.081)	(0.059)	(0.124)	(0.099)
$AI(t-1)$	0.065	-0.001	0.038	0.003
	(0.090)	(0.020)	(0.034)	(0.036)
$AI(t-2)$	0.097	0.002	0.052	0.047**
	(0.066)	(0.048)	(0.036)	(0.023)
$Robots(t)$	0.095***	-0.021	-0.018	0.058
	(0.029)	(0.036)	(0.031)	(0.037)
$Robots(t-1)$	0.007	0.034	-0.001	-0.002
	(0.024)	(0.027)	(0.015)	(0.012)
$Robots(t-2)$	0.001	0.039	0.007	0.019
	(0.017)	(0.032)	(0.009)	(0.013)
Intercept	0.927	1.949*	0.860	2.002
	(2.495)	(1.138)	(1.174)	(1.284)
Time dummies	Yes	Yes	Yes	Yes
Observations	319	319	319	319
AR(1)	0.000	0.001	0.005	0.000
AR(2)	0.455	0.954	0.601	0.233
Hansen	0.394	0.305	0.119	0.101

Notes: Robust standard errors in parenthesis, clustered at country-level.
** p < 0.10 ** p < 0.05 *** p < 0.01*

Table 4 – $U_{i=2}$ differentiated by age group - GMM-SYS estimates

	$U_{i=2}^{k=25-34}$	$U_{i=2}^{k=35-44}$	$U_{i=2}^{k=45-54}$	$U_{i=2}^{k=55-64}$
$U_i^k(t-1)$	0.131	-0.059	-0.029	-0.186**
	(0.127)	(0.124)	(0.067)	(0.091)
$Y(t)$	-0.567***	-0.466***	-0.379***	-0.289**
	(0.162)	(0.079)	(0.100)	(0.057)
$Y(t-1)$	-0.108	-0.227***	-0.211***	-0.305***
	(0.068)	(0.069)	(0.062)	(0.058)
$IR_i^k(t)$	-0.090	-0.099	0.118	-0.081
	(0.422)	(0.121)	(0.108)	(0.055)
$IR_i^k(t-1)$	-0.190	0.008	-0.278**	-0.083
	(0.142)	(0.163)	(0.128)	(0.051)
$AI(t)$	0.001	-0.086**	-0.056	0.009
	(0.066)	(0.033)	(0.042)	(0.026)
$AI(t-1)$	0.033	-0.028	-0.025	-0.067**
	(0.069)	(0.032)	(0.021)	(0.026)
$AI(t-2)$	0.032	0.023	0.017	0.000
	(0.037)	(0.024)	(0.017)	(0.022)
$Robots(t)$	0.037***	0.059***	0.072***	0.020*
	(0.011)	(0.021)	(0.018)	(0.010)
$Robots(t-1)$	0.016	-0.034**	-0.009	0.012
	(0.017)	(0.013)	(0.015)	(0.012)
$Robots(t-2)$	-0.007	-0.017**	-0.015*	-0.004
	(0.012)	(0.007)	(0.008)	(0.010)
$Intercept$	-0.709	1.827**	0.815	0.942
	(1.592)	(0.840)	(0.782)	(0.798)
Time dummies	Yes	Yes	Yes	Yes
Observations	319	319	319	319
AR(1)	0.001	0.000	0.000	0.002
AR(2)	0.624	0.120	0.764	0.491
Hansen	0.207	0.484	0.283	0.286

Notes: Robust standard errors in parenthesis, clustered at country-level.
** p < 0.10 ** p < 0.05 *** p < 0.01*

Table 5 – $U_{i=3}$ differentiated by age group - GMM-SYS estimates

	$U_{i=3}^{k=25-34}$	$U_{i=3}^{k=35-44}$	$U_{i=3}^{k=45-54}$	$U_{i=3}^{k=55-64}$
$U_i^k(t-1)$	-0.094	-0.010	-0.007	-0.283**
	(0.099)	(0.099)	(0.070)	(0.106)
$Y(t)$	-0.300***	-0.092	-0.105***	-0.047
	(0.087)	(0.057)	(0.057)	(0.045)
$Y(t-1)$	-0.112**	-0.139**	-0.110***	-0.189***
	(0.046)	(0.060)	(0.034)	(0.048)
$IR_i^k(t)$	0.545**	0.097	-0.399*	-0.011
	(0.081)	(0.233)	(0.222)	(0.043)
$IR_i^k(t-1)$	-0.057	0.112	-0.015	-0.065
	(0.087)	(0.103)	(0.089)	(0.039)
$AI(t)$	0.044	0.011	-0.013	0.028
	(0.034)	(0.039)	(0.015)	(0.025)
$AI(t-1)$	-0.009	-0.065	0.066	-0.041**
	(0.021)	(0.039)	(0.052)	(0.019)
$AI(t-2)$	-0.039**	0.000	0.026*	0.012
	(0.018)	(0.024)	(0.014)	(0.027)
$Robots(t)$	0.007	0.021*	0.016	0.037***
	(0.013)	(0.010)	(0.010)	(0.013)
$Robots(t-1)$	0.002	0.028*	-0.002	0.018
	(0.008)	(0.014)	(0.006)	(0.013)
$Robots(t-2)$	0.009	-0.010	-0.002	-0.012
	(0.006)	(0.009)	(0.004)	(0.009)
Intercept	0.357	0.485	-0.945	-0.146
	(0.637)	(0.699)	(0.826)	(0.492)
Time dummies	Yes	Yes	Yes	Yes
Observations	319	319	319	319
AR(1)	0.002	0.001	0.004	0.001
AR(2)	0.784	0.503	0.233	0.131
Hansen	0.224	0.221	0.268	0.332

Notes: Robust standard errors in parenthesis, clustered at country-level.
** p < 0.10 ** p < 0.05 *** p < 0.01*

Lastly, we note that the most robust of the effects highlighted in Tables 1 and 2 is the positive correlation between the stock of robots and the unemployment rates of people with a medium level of education ($U_{i=2}^{k=25-64}$). The correlation is indeed positive and statistically significant for every age group. On the other hand, the effect of AI on unemployment is not very robust: while we can observe an effect on $U_{i=2}^{k=25-64}$, it is no longer visible when we disentangle this unemployment rate by age groups. The negative correlation with $U_{i=1}^{k=25-64}$ is also a bit surprising, and would imply that there is a complementarity between low-skilled workers and *AI* technologies. While this can

make sense for some specific tasks, as for example labelling some data that will then be used to train a supervised learning algorithm, it is harder to find an explanation for this relation at the macro level.

Based on the results obtained, we can now answer the four research questions formulated in section 2. First, we can validate H1 (a positive correlation between *Robots* , *AI* and *U*). Indeed, the results presented in Table 1 indicate that *Robots*(*t*) and *AI*(*t* – 2) are positively correlated with the aggregate unemployment rate, and the effect of robots is also found in Table 1 and 2 when we run the regressions on unemployment rates differentiated by education level.

Secondly, we can conclude that H2 (positive correlation between robots and U1 and negative correlation between robot and U3) is not validated. Indeed, we find a positive correlation between robots and unemployment rate for all three education groups. It should be noted, however, that the magnitude of the correlation decreases along with the level of education, with a coefficient that is 1.34 times higher for the less educated than for the most educated. This result is interesting because it goes against the popular opinion which holds that robotics constitute a "skill-based technical change" that is detrimental to the less educated and beneficial to those with more skills. At the macro level and according to our estimates, it is detrimental for all types of workers, but only slightly less so for those who are skilled.

The third hypothesis (H3), postulating that robots and AI mainly impact the unemployment rate of people with a medium level of education, is only partially validated. Over a three-year period, we note that the net effect of *AI* is positive (thus increasing unemployment) only for $U_{i=2}^{k=25-64}$, while the effect on $U_{i=1}^{k=25-64}$ is negative and no significant effects are found for $U_{i=3}^{k=25-64}$ (Tables 1 and 2). We note, however, that this positive effect disappears when we run the regressions by age groups. Regarding robots, the evidence is more solid, with a 1% increase in the robot stock associated with a 0.041 increase of $U_{i=2}^{k=25-64}$ over a three-year period, while the effect is 0.035 and 0.026 for $U_{i=1}^{k=25-64}$ and $U_{i=3}^{k=25-64}$ respectively. When we disentangle $U_{i=2}^{k=25-64}$ by age groups, we notice that the positive effect of robots is present in all four categories.

The last hypothesis H4 (a positive correlation between robots and $U_{i=1}^{k=25-34}$ and a negative or not significant effect on the unemployment rate of older people with the same education), and a negative correlation between AI and $U_{i=3}^{k=25-34}$(and a positive or not significant effect on the unemployment rate of seniors with the same level of education) is only partially validated. While we indeed find that robots are positively correlated with $U_{i=1}^{k=25-34}$ and not with $U_{i=1}^{k=55-64}$ (Table 3), we also find that AI is negatively correlated with both $U_{i=3}^{k=25-34}$ and $U_{i=3}^{k=55-64}$ (Table 5). This result could imply that the "experience" effect is stronger than the "knowledge obsolescence" effect.

Concluding Remarks and Issues for Further Research

Using panel data on 33 OECD countries, we have investigated the link between AI, robots and unemployment. We have found that both robots and AI tend to increase unemployment (Table 1), providing additional evidence to the literature on technological unemployment. We reran the regression on unemployment rates differentiated by education level and age group, and found a strong heterogeneity in the effects of AI and robots (Table 1 to 5). Some effects highlighted at the aggregate level, such as the impact of robots on the unemployment rate of those with the lowest levels of education, seem to be concentrated only on some age groups (in this example the 25-34 year-olds). This analysis at the intersection of education and age (as proxies for qualification and experience) brings new elements to the literature by showing that the low/medium/high skilled dichotomy is an overly simplistic framework for studying the effect of these technologies on employment. Finally, we show that the effects of robots are the strongest on the unemployment rate of people with a medium level of education, which supports findings from the literature on technological change-induced labor market polarization. We also find that, over a three-year period, AI increases the unemployment rate of people with a medium level of education (Table 2) while the effect is negative or not significant for the others (Table 1 and 3, respectively), but the result is not very robust as it is no longer observable when we disentangle the unemployment rates by age groups. As discussed in the previous section on data and methodology, the use of patents as a proxy for technological capabilities is questionable. A better way to assess the effect of AI on non-employment would consist in using data on the stock of AI-related software and algorithms. Unfortunately, such data do not exist at the macro level; a first approximation is to use data on the stock of software and databases published by national statistical offices but it is not yet possible to know what part of this stock includes AI-related software. For robots, data on service robots (medical robots, automated vehicles, etc.) would be needed to obtain a more complete estimate of the overall stock of robots. It would also be interesting to assess whether, as in the case of industrial robots, the relationship between service robots and unemployment is null or if some effects can be identified. Lastly, a longer period of time is needed to observe the effects of these two technologies on unemployment in the long run.

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Appendix

Table A1 – $U_{i=1}$ differentiated by age group—Fixed effect estimates

	$U_{i=1}^{k=25-34}$	$U_{i=1}^{k=35-44}$	$U_{i=1}^{k=45-54}$	$U_{i=1}^{k=55-64}$
$U_i^k(t-1)$	-0.191*	-0.178**	0.010	-0.176*
	(0.099)	(0.067)	(0.085)	(0.070)
$Y(t)$	-0.555***	-0.523***	-0.598***	-0.300**
	(0.057)	(0.149)	(0.140)	(0.084)
$Y(t-1)$	-0.548***	-0.334***	-0.208***	-0.226***
	(0.093)	(0.101)	(0.093)	(0.037)
$IR_i^k(t)$	0.165*	-0.024	0.172	0.155*
	(0.084)	(0.086)	(0.105)	(0.088)
$IR_i^k(t-1)$	0.003	0.023	0.017	0.106*
	(0.120)	(0.073)	(0.144)	(0.058)
$AI(t)$	-0.087	-0.058	-0.000	-0.096
	(0.058)	(0.055)	(0.081)	(0.058)
$AI(t-1)$	0.043	0.002	0.038	-0.025
	(0.057)	(0.035)	(0.024)	(0.035)
$AI(t-2)$	0.033	-0.006	0.030	-0.001
	(0.054)	(0.041)	(0.020)	(0.024)
$Robots(t)$	0.024	0.004	-0.003	0.029**
	(0.015)	(0.011)	(0.006)	(0.014)
$Robots(t-1)$	0.005	0.033*	0.004	-0.001
	(0.008)	(0.016)	(0.015)	(0.009)
$Robots(t-2)$	0.007	0.024	-0.002	0.021**
	(0.012)	(0.028)	(0.007)	(0.009)
Intercept	-0.277	0.498	-0.192	1.420*
	(1.515)	(1.134)	(0.790)	(0.795)
Time dummies	Yes	Yes	Yes	Yes
Observations	319	319	319	319
R^2	0.5179	0.4378	0.4353	0.3526

Notes: Robust standard errors in parenthesis, clustered at country-level.
** p < 0.10 ** p < 0.05 *** p < 0.01*

Table A2 – $U_{i=2}$ differentiated by age group—Fixed effect estimates

	$U_{i=2}^{k=25-34}$	$U_{i=2}^{k=35-44}$	$U_{i=2}^{k=45-54}$	$U_{i=2}^{k=55-64}$
$U_i^k(t-1)$	0.091	0.022	0.041	-0.077
	(0.063)	(0.074)	(0.076)	(0.086)
$Y(t)$	-0.480***	-0.384***	-0.347***	-0.262**
	(0.051)	(0.051)	(0.062)	(0.045)
$Y(t-1)$	-0.146***	-0.166***	-0.155***	-0.259***
	(0.069)	(0.035)	(0.043)	(0.067)
$IR_i^k(t)$	0.025	-0.106	0.024	-0.049
	(0.075)	(0.111)	(0.165)	(0.047)
$IR_i^k(t-1)$	-0.149*	-0.008	-0.064	-0.041
	(0.075)	(0.110)	(0.101)	(0.038)
$AI(t)$	-0.015	-0.021	-0.019	-0.001
	(0.028)	(0.026)	(0.024)	(0.020)
$AI(t-1)$	-0.038*	-0.017	-0.012	-0.043**
	(0.020)	(0.021)	(0.025)	(0.019)
$AI(t-2)$	0.043*	0.024	0.012	0.017
	(0.024)	(0.016)	(0.013)	(0.016)
$Robots(t)$	0.010*	0.020**	0.020***	0.002
	(0.005)	(0.009)	(0.005)	(0.004)
$Robots(t-1)$	-0.006	-0.021***	-0.002	0.011
	(0.006)	(0.004)	(0.005)	(0.008)
$Robots(t-2)$	-0.008	-0.004	-0.003	-0.003
	(0.005)	(0.010)	(0.008)	(0.010)
Intercept	0.542	0.898	0.680*	0.409
	(0.653)	(0.664)	(0.368)	(0.527)
Time dummies	Yes	Yes	Yes	Yes
Observations	319	319	319	319
R^2	0.6294	0.5760	0.5895	0.5173

Notes: Robust standard errors in parenthesis, clustered at country-level.
** p < 0.10 ** p < 0.05 *** p < 0.01*

Table A3 – $U_{i=3}$ differentiated by age group—Fixed effect estimates

	$U_{i=3}^{k=25-34}$	$U_{i=3}^{k=35-44}$	$U_{i=3}^{k=45-54}$	$U_{i=3}^{k=55-64}$
$U_i^k(t-1)$	0.009	-0.106	-0.105**	-0.218**
	(0.094)	(0.099)	(0.046)	(0.084)
$Y(t)$	-0.273***	-0.147***	-0.129***	-0.058***
	(0.072)	(0.037)	(0.020)	(0.017)
$Y(t-1)$	-0.093**	-0.140***	-0.102***	-0.173***
	(0.042)	(0.031)	(0.028)	(0.047)
$IR_i^k(t)$	0.082	0.101	-0.109*	-0.028
	(0.085)	(0.123)	(0.062)	(0.034)
$IR_i^k(t-1)$	-0.014	0.020	-0.056	0.034
	(0.073)	(0.081)	(0.065)	(0.033)
$AI(t)$	0.014	0.013	-0.008	0.020
	(0.018)	(0.012)	(0.010)	(0.021)
$AI(t-1)$	0.002	-0.005	0.011	-0.023
	(0.020)	(0.010)	(0.013)	(0.017)
$AI(t-2)$	0.010*	-0.002	0.016	0.018
	(0.014)	(0.018)	(0.010)	(0.018)
$Robots(t)$	-0.002	0.000	0.011*	0.017***
	(0.012)	(0.005)	(0.006)	(0.005)
$Robots(t-1)$	0.001	0.007	0.001	0.017*
	(0.005)	(0.007)	(0.004)	(0.010)
$Robots(t-2)$	0.010*	-0.002	-0.003	-0.006
	(0.005)	(0.005)	(0.003)	(0.007)
Intercept	0.159	0.253	-0.122	-0.426*
	(0.393)	(0.319)	(0.208)	(0.216)
Time dummies	Yes	Yes	Yes	Yes
Observations	319	319	319	319
R^2	0.4423	0.3990	0.4955	0.3174

Notes: Robust standard errors in parenthesis, clustered at country-level.
** p < 0.10 ** p < 0.05 *** p < 0.01*