Robotization, employment, and income: regional asymmetries and long-run policies in the Euro area

Enzo Valentini[1] · Fabiano Compagnucci[2] ⬤ · Mauro Gallegati[3] · Andrea Gentili[4]

Abstract

This work correlates the impact of robotization on employment and households' income at the regional scale with the level of investment in R&D and education policies. This kind of policy, by raising the qualitative and quantitative levels of human capital, contributes to improving the complementarity effect between humans and robots, thus mitigating the substitution effect. To this end, we compute the Adjusted Penetration of Robots (APR) (a metric used to measure the extent to which robots are being used in a particular industry or sector) at the sectoral level, combining the International Federation of Robotics database for the stock of robots, EUROSTAT Regional database, and the STructural ANalysis database on 150 NUTS-2 regions of the Euro area. We then perform a spatial stacked-panel analysis on the investment in R&D and education level. Results supports the idea that regions that invest more in R&D and have higher levels of human capital can turn the risk of robotization into an increase in both income and "quantity of work," by enhancing complementarity between robots and the labor force. On the contrary, regions investing less in R&D and having lower levels of human capital may suffer a reduction in households' disposable income.

Keywords Robotization · Employment · Households' income · R&D policies · Adjusted Penetration of Robots (APR) · Education policies · Regional inequalities

JEL classification O33 · J24 · D02 · R23

1 Introduction

Since the start of the 2008 financial crisis, "European countries have variously faced economic stagnation, rising inequalities, worsening social conditions, and strains on public services" (della Porta 2021, p. 325), exacerbated by a polarization process resulting in

Enzo Valentini contributed equally to this work.

✉ Enzo Valentini
   enzo.valentini@unimc.it

Extended author information available on the last page of the article

the spatial concentration of economic development, wealth, and population (Görmar et al. 2019). In terms of macro areas, we are witnessing a concentration of employment, skills, competitiveness, and industrial specialization in a "German-centered core" whereas the "Southern periphery" is lagging behind (Cirillo and Guarascio 2015). However, diverging trajectories also arise at a lower scale. After a period of relative convergence until the end of the 1980s, EU regional inequalities have importantly increased in the new millennium (Storper 2018; Fratesi and Perucca 2019), resulting in a complex patchwork of spatial patterns: income and employment differ not only between states and regions but also between core and peripheral areas within the same region, as well as between dynamic metropolitan regions and stagnating ones (Iammarino et al. 2019).

These growing inequalities are at the core of an intense debate (Piketty 2013; Alvaredo et al. 2017; Stiglitz 2013), which identifies among their main causes the impetuous technological development that has occurred over the last 40 years (Autor et al. 2003; Hanson and Harrison 1995; Jovanovic 2009; Van Reenen 2011), of which robotization represents one of the most notable steps. As a matter of fact, the recent technological development has produced such structural changes as to upset the patterns of development of modern economies. Within this debate, the robotization of the production process has assumed relevance, renewing the discussion between techno-optimists (Caselli et al. 2021; Ballestar et al. 2020; Graetz and Michaels 2018; Dauth et al. 2019; Brynjolfsson and McAfee 2014; Mokyr 2010; Jovanovic and Rousseau 2005) and techno-pessimists (Fernald 2014; Manyika et al. 2017; Gordon 2012; Arntz et al. 2016; Frey and Osborne 2017), as Andrews et al. (2016) suggest.

Technological change, in fact, causes structural change, which directly affects regional economies (Gräbner et al. 2020) and, as a result, indirectly translates into variations of the aggregate and sectoral demand for goods and services. Accordingly, Compagnucci et al. (2022) empirically show that the structural composition of regional economies has been one of the main causes of the asymmetric effects of the 2008 financial crisis. In this regard, what makes the difference is the capacity of a region to lead and shape the technological change or, on the contrary, to passively suffer its effects. In other words, the impact of robotization on employment and income will depend on the regional capacity to maximize the complementarities between humans and robots, while minimizing the substitution effect. Obviously, the level of human capital and of specific economic activities (i.e., high-tech manufacturing and knowledge intensive services), which are unevenly distributed across regions, plays a crucial role in this sense. Still, the presence of these factors is importantly affected by regional policy concerning R&D and education levels.

The recent rise of the smart specialization strategy within the EU regional and urban policy reforms (McCann and Ortega-Argilés 2016) is a case in point, since it aims at strengthening research, technological development, and innovation at the regional level. The same applies to the commonly known "Industry 4.0" strategy, which encourages industrial sectors to adopt the new technologies to move towards higher-value digitized products and processes, supported by regional and local authorities[1]. Given the level of knowledge and skills that this type of specialization

---

[1] https://ec.europa.eu/commission/presscorner/detail/fr/SPEECH_15_4772

requires, education policies take on particular importance, although a different mix of competencies between local and national governments in the EU countries[2]. For instance, in Italy, secondary school is a matter of regional authorities, whose decision-making process is based on local peculiarities and needs (Bruno et al. 2022). This policy thus has consequences in terms of accessibility, not only to secondary but also to tertiary education, as well as in coping with the possible mismatch between the skills provided by the education system and those required by the regional labor market. By doing so, it can help create the conditions for the complementarity effect between human beings and machines. On the contrary, in case of their poor design due to budgetary constraints or lock-in in public decision-making, the substitution effect could prevail with negative outcomes in terms of citizens' welfare. These conclusions draw attention to the need for regional place-based policies in the EURO area, so that the robotization process does not turn out to be yet another shock harbinger of territorial inequalities (Aghion et al. 2019).

Despite the importance of robotisation in our societies, contributions on the topic tend to be anecdotal and focused on productivity and employment outcomes at the macro and national levels only, also due to the lack of data on robot at a regional scale (Green Leigh and Kraft 2017). This implies little attention to the regional level and related policies, which, in contrast, is the context where policy makers must not only respond to potential employment losses but also propose strategies to remain competitive in the changed contextual conditions.

Against this background, the aim of our work is to contribute to the debate by showing how the outcomes of robotization at the regional level are conditioned by long-term policy choices such as the investment in R&D and the capacity of the education system to raise the qualitative and quantitative level of human capital. Our analysis of the Euro Area regions in the last 20 years shows that there is a positive interaction between the abovementioned policies and the robotization process of the different industrial sectors. While, in general, a higher exposure of European regions to robotization, computed according to Acemoglu and Restrepo (2020), has compressed households' income against non-significant positive effects on employment, those regions that have invested more in R&D and human capital have been able to more than compensate for the income losses and to improve employment levels. These results support the idea that regional policies play a key role in influencing regional development trajectories, and that, if well designed, they can help mitigate the negative externalities generated by the robotization process.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 discusses the data employed and the empirical strategy. Section 4 discusses the main results, whereas Section 5 provides some final remarks.

2 R&D, education, and robotization

In 1969, Atikinson and Stiglitz, breaking with neoclassical orthodoxy, argued that improvements in technology could have affected the use (and hence the remuneration) of the different factors of production in a non-uniform manner, thus violating

---

[2] https://www.ccre.org/docs/Local_and_Regional_Government_in_Europe.EN.pdf

the assumption of technological neutrality proposed by Hicks (Acemoglu et al. 2015). Such predictions came true in the late 1980s, when an unprecedented growth in R&D investment and in the use of technology in the production process occurred (Kim and Nelson 2000; McConnell and Perez-Quiros 2000). These processes jointly caused a structural shift towards more innovation- and knowledge-oriented sectors in advanced countries (van Winden 2007; Raspe and Van Oort 2006; Florida 2002).

According to Acemoglu (1999), this radical change had a substantial impact on income distribution. Since technological progress is fundamentally based on competencies, it has mainly rewarded the most skilled and educated workers, while replacing with machines the less skilled and poorly educated, who perform repetitive work. Acemoglu and Loebbing (2022), by developing an assignment model of automation, show that automation occurs (regarding medium-skilled competencies) when: (1) high-skilled workers have a comparative advantage relative to capital in complex tasks; and (2) low-skilled workers' compensations are lower than their productivity and the cost of capital for their replacement. If the cost of capital decreases (or its productivity increases), then we will experience more automation, pushing workers at the top and the bottom of the task distribution. This finally leads to unemployment, wage polarization, and a reduction in real wage of workers at risk of substitution. These theoretical considerations are empirically discussed by Acemoglu and Restrepo (2021), who argue that the changes that occurred in the US wage structure in the last 40 years depended between 50% and 70% on the relative wage decline of workers doing repetitive tasks. These theoretical considerations are discussed empirically by Acemoglu and Restrepo (2021), who argue that the changes in the wage structure in the United States over the past 40 years have been 50%-70% dependent on the relative wage decline of workers performing repetitive tasks in sectors which experienced a rapid automation.

Such results have important spatial implications. The endowment of physical and human capital, in fact, is not uniform across regions and factors' mobility is far from the perfect one predicted by neoclassical models. Highly skilled and educated workers are concentrated in some of the largest urban and metropolitan regions of advanced countries (Krätke 2007; Florida 2002; Moretti 2012, 2013). Baum-Snow and Pavan (2012) show that the overall increase in the spatial divide of wages that occurred between 1979 and 2007 in the United States was significantly correlated with city size, which positively affected nominal wages, housing prices, and productivity. Kemeny et al. (2022), using the universe of patents between 1920 and 2010 in the US, found that disruptive innovation (as robotization is) is spatially clustered at its outbreak and plays a substantial role in regulating overall patterns of spatial output and income inequality. Thus, since technological progress is localized (Atikinson and Stiglitz 1969) and benefits from scale and agglomeration economies, it tends to polarize the distance between regions endowed with different levels of physical and human capital (Fleisher et al. 2010).

Recently, the processes of polarization within and between social groups and regions has often been associated with the process of automation (Brynjolfsson and McAfee 2011; Graetz and Michaels 2017; Manyika et al. 2017), particularly in the

manufacturing sector, where industrial robots operate. By industrial robot (definition ISO 8373 - International Federation of Robotics 2020) we mean an automatically controlled, programmable, multi-purpose manipulator, mobile on three or more axes. Based on five different types of kinematics, the modern industrial robot is the extreme evolution of the mechanical spinning machine generally identified, together with the railway, as the symbol of the First Industrial Revolution. A robot, however, differs significantly from the mechanical spinning machine, and from all the production automation technologies that have followed since 1700, since it is reprogrammable and usable for different purposes.

Robots, in short, contain not only "capital", but also "work", since they are able to perform different functions almost (if not totally) independently. They represent, potentially, a new type of worker that requires hardware and software maintenance but at the same time allows the elimination of all the costs linked to human "weaknesses" (from the need for breaks, rest shifts, sick leave, and holidays, to salary claims), which have negative effects on productivity and profits. It is no coincidence that the COVID-19 pandemic has pushed towards the robotization and automation almost all types of industries (Lund et al. 2020). Robots are, indeed, potential substitutes for human workers. Undoubtedly, industrial robots allow to produce more (when not even to perform tasks otherwise impossible for humankind) in less time, with fewer errors and lower costs than human labor (Dauth et al. 2019; Graetz and Michaels 2018). However, the literature does not agree on the possible economic and social consequences of the adoption of such technology in all productive activities currently performed by humans (see Mondolo 2021 for a comprehensive discussion of the relevant literature).

The positivist view generally identifies six possible mechanisms through which the adoption of capital goods allows increasing productivity while maintaining constant (when not increasing) the demand for labor. Specifically, this can occur in conjunction with: (1) the creation of employment in the sector that produces robots meant to replace the human workforce (Say 1964); (2) the reduction of production costs in the sector that adopts the robots, which results in a reduction of the output price and, therefore, in the possible expansion of the sector itself (Hall and Hefferman 1985); (3) a situation of non-instantaneous competitive convergence generating extra profits and allowing capital accumulation which in turn can boost investments and, ultimately, positive employment effects (Van Reenen 1997); (4) the lowering of wages allowing the reabsorption of workers in other sectors (Pigou 1933); (5) the generation of positive externalities related to the increase in income, which in turn stems from increased productivity (see Piva and Vivarelli 2017a for a detailed discussion of these issues); (6) the introduction of new goods and services and therefore the creation of new business sectors (Schumpeter 1918).

However, as Freeman (2016) writes: "There is [...] nothing in economics that guarantees that the humans displaced from jobs by robots will end up with new jobs that pay as much as their former jobs [...]". In this regard, the literature has already shown how technological innovation can act as a dislocating force of labor when the expansion of the sectors involved is not fast enough. This can happen for different reasons: due to institutional constraints (Herwartz and Niebuhr 2011), or input shortages (Attinasi et al. 2021), but also in the presence of mature

sectors and saturated markets unable to expand their output (Bessen 2019). Moreover, the negative effect of technological innovation on employment and income may prevail in the absence of income-oriented public support for unemployment, training of workers, and stimulation of demand for the new emerging sectors (Delli Gatti et al. 2012). As pointed out by Acemoglu and Restrepo (2020), the same technology may boost employment or can reduce the demand for labor according to the capacity of the industry and workers to move to non-automated tasks faster than the pace of automation.

Hence, even robotization corroborates the soundness of the theoretical shift from a neutral technological change towards a "biased and directed technological change" which, in addition, is importantly localized (Acemoglu et al. 2015, p. 445). It follows that, as Nuccio et al. note (2020), more than assessing the direct employment impact of robotization, it is worth considering the polarization effect "between economies that grow because of the early adoption of automation (and associated organizational change) and economies that shrink because they were not able to catch up" (p. 5). Regional systems, in conclusion, can facilitate or hinder the adoption of new technology and the rise of new sectors, and institutions can play an important role in such a context (Nuccio et al. 2020).

Focusing on policies, several macro-strands arise in the literature. The first one concerns the investment in R&D, which may produce effects on points (1) and (6) of the positivist view previously outlined. The second regards policies aiming at strengthening the comparative advantage of the labor force, such as the financing of the education and training systems, which allows a qualitative-quantitative improvement of human capital, promoting the complementarity between labor and machine (point 5 of the positivist view). Both of these types of policies generally suffer from underinvestment, the level of which also depends on the different public–private mix that characterizes each economic system. R&D expenditure, for instance, results from both public and private investments. Although it is aimed at a specific goal (increasing the innovation level at the micro and macro levels), it generates a series of positive externalities for the whole community. However, as it is well established in the literature since Arrow (1972), private firms, in order to maximize their profit, usually invest in R&D less than the optimal value for the social planner. It follows that, where R&D expenditure primarily results from the private sector, the beneficial externalities for the community could be under-sized. In these cases, a direct action by the policy makers could be necessary.

Other kinds of polices were proposed to deal with robotization. About robot taxation, for instance, Zhang (2019) finds that it unconditionally reduces wage inequality, both with or without the presence of a labor union in the automated sector, and when introducing a regulated wage rate in that sector. In addition, the collective ownership of robots, along with the introduction of a universal income (which is further useful to support the aggregate demand during transition phases), as well as the management of the working time (Cséfalvay 2019; Belloc et al. 2020) could also be effective in mitigating the negative effects of robotization. However, unlike education/training and R&D expenditure policies, cases regarding the adoption of these policies are very limited and even less are the available data. Therefore, these options are not considered here.

On the contrary, the planning and adoption of R&D and education policies are unanimously reputed to be crucial, resulting in being more widespread, and thus

allowing spatial comparisons. Already in 2010, the European Commission (2010) pointed out that even in times of fiscal austerity, there was a need to invest in education, R&D, innovation, and ICT in order to maintain the capacity to create employment and ensure the welfare of European citizens. For R&D, given the under-investment in knowledge (as a percentage of GDP) of the EU average (0.8% lower than in the USA and 1.5% lower than in Japan), it was believed that reaching the threshold of 3% of GDP would have allowed an increase in employment of about 3.7 million jobs.

Although the 3% target has not been reached[3], nevertheless some researchers have highlighted a statistically significant relationship between R&D expenditure and employment performance, even though, in most cases, net of the heterogeneous effects arising from different sectors. Indeed, technological change and firm innovation "in some parts of the economy may either stimulate or come at the expense of employment in others" (Herstad and Sandven 2019, p. 376). Piva and Vivarelli (2017b), for example, based on a firm-level database including the largest European R&D investors in the period 2002 to 2013, find a positive relationship between the two variables. This relationship, however, only holds for high- and medium-tech manufacturing. In line with these results and with reference to a representative sample of Spanish manufacturing firms between 2002 and 2013, Pellegrino et al. (2019) show how this positive relationship only concerns high-tech manufacturing. Bogliacino et al. (2012), analyzing data concerning 677 European firms in the period between 1990 and 2008, obtain very similar results, and thus positive and significant effects in terms of R&D-related employment in the high-tech manufacturing and services sectors only, with zero effects on medium-low-tech manufacturing. Ciarli et al. (2018), with reference to the English Travel to Work Areas, highlight two underlying dynamics. On the one hand, the increase in R&D investment in functional areas with more routine jobs had negative effects in sectors with low-skilled employment, especially in non-tradable sectors (as transport and construction) and in services, but, at the same time, exerted a positive effect on the self-employment of younger workers. On the other hand, in functional areas with a lower rate of routine work, a positive relationship emerges between R&D and the demand for high-skilled workers versus a reduction in demand for low-skilled workers. Similarly, Aldieri et al. (2021), analyzing the regional expenditure in Finland between 2000 and 2013, find positive effects only for the demand of high-skilled jobs, but negative effects for low-skilled jobs. If, on the one hand, such empirical evidence clearly corroborates the effort of EU policies in stimulating R&D, on the other hand it highlights the potential risks for low-tech manufacturing, which still plays an important role in Europe, requiring a coordination effort with education policies to address the issue of low-skilled workers, as well as the need to introduce innovation within low-tech manufacturing (Cardamone et al. 2018).

There is ample evidence in the literature on how spending on R&D, education, and training of workers creates positive societal externalities. Increased investment in R&D should, in principle, facilitate the transition towards the technological frontier (Lee 2009; Hall et al. 2013) by exploiting and expanding the margins of complementarity between

---

[3] In 2020, according to Eurostat, EU R&D expenditure stood at 2.32% of GDP. https://ec.europa.eu/eurostat/databrowser/view/tsc00001/default/table?lang=en

humans and machines. This also allows to benefit directly from the production of the capital goods underlying the 4IR, or from the creation of new business sectors made possible by technological advancement. Furthermore, increased investment in R&D should raise the demand for a more highly educated and skilled workforce (Autor et al. 1998), thereby augmenting the positive externalities exerted by the knowledge economy (OECD 1996; Engelbrecht 1997) with consequent multiplier effects on employment and wages.

Nonetheless, the role of human capital in avoiding or mitigating the employment costs associated with the automation of production processes is a well-known issue. Lankisch et al. (2019) empirically show that automation is responsible for the wage decline of non-skilled workers and, potentially, of the skilled ones, and for the raise of the skill premium. Its capacity to affect income inequality stresses the importance of investing in higher education, which, in turn, by preventing the substitution effect, increases the share of population benefiting from the automation-driven economic growth.

The hypotheses of skill-biased technological change (Acemoglu and Autor 2011) and of routine-biased technological change (Autor et al. 2003) are intrinsically linked to the need to increase the qualitative and quantitative level of human capital through education and retraining of the workforce where necessary. Against the automation process, the acquisition of new skills and abilities would allow workers to fill earlier non-automated occupations and/or functions, similarly to what happened with the migration of the workforce from the primary sector to industry following the mechanization of agriculture (Delli Gatti et al. 2012). Acquiring new skills would allow workers to "migrate" more easily to activities that are complementary with those that are automated. Although the two strands of literature differ substantially in the specific role attributed to skills and abilities versus tasks[4], both give human capital a central role. The inability of economic systems to provide for the needs of continuing education and (re)training becomes, *de facto*, one of the causes of worker dislocation and increasing inequality (Acemoglu and Restrepo 2018).

3 Robotization in European regions

To create a reliable proxy for regional exposure to robotization, we calculate the metric Adjusted Penetration of Robots (APR) at the sectoral level, following the approach suggested by Acemoglu and Restrepo (2020). For this purpose, we use two databases: the International Federation of Robotics (IFR) and the STructural ANalysis databases (STAN OECD).

3.1 Sectoral adjusted penetration of robots (APR)

The first step of the analysis consists of providing a measure for the APR at industry (i) level, in a given country (Italy = IT, for example), from t_0 to t_1. Specifically, according to Acemoglu and Restrepo (2020), the following specification is proposed:

---

[4] In particular, due to the diffusion of ICTs during the Third Industrial Revolution (Mondolo 2021).

$$\overline{\text{APR}}^{\text{IT}}_{i,(t_0,t_1)} = \frac{M_{i,t_1} - M_{i,t_0}}{L_{i,t_0}} - g_{i,(t_0,t_1)} \frac{M_{i,t_0}}{L_{i,t_0}} \tag{1}$$

where, M is the stock of robots (IFR), L is the number of persons employed (per 100,000) (STAN), g is the growth rate of the output (STAN).

This measure of robots' penetration combines the industry-level variation in the usage of robots, baseline employment shares, and an adjustment for the overall expansion of each industry's output, given by the last term of the equation.

Acemoglu and Restrepo (2020) calculate APR at the US level and the average of five European countries (Denmark, Finland, France, Italy, and Sweden). In general, it is possible to compute this average for N countries:

$$\overline{\text{APR}}^{\text{Ncountries}}_{i,(t_0,t_1)} = \frac{1}{N} \sum_{j \in N} \left[\frac{M^j_{i,t_1} - M^j_{i,t_0}}{L^j_{i,t_0}} - g^j_{i,(t_0,t_1)} \frac{M^j_{i,t_0}}{L^j_{i,t_0}} \right] \tag{2}$$

In our analysis, we consider nine countries (Austria, Belgium, Finland, France, Germany, Greece, Italy, Netherlands, and Portugal) whose base value results from the average of their concerned industries (as defined by IFR) in t_0. Table 1 reports the calculation of APR, namely the change in robot usage per 100,000 employees according to the different industries considered. Following Acemoglu and Restrepo (2020), and according to the fact that the effect of robotization may take some years to have an impact on economic variables and that APR yearly variation may be misleading, we undergo staked differences analysis. We therefore divide the period into four main sub-periods: 2000–2004, 2004–2008, 2008–2012, and 2012–2017. This allows us to have two periods before and two periods after the 2008 financial crisis. Moreover, according to Acemoglu and Restrepo (2020), we imputed "non-specified" robots from the IFR database to sectors according to their distribution in each country.

Before describing the empirical strategy, it is necessary to discuss some preliminary peculiar values. The value 0 in "Chemicals and pharmaceutical products" is the result of a variation equal to 0 in the stock of robots in the first two periods under analysis. This result can hardly be explained by the literature on patents that identifies the pharmaceutical sector as one of the sectors more exposed to labor-saving innovations (Montobbio et al., 2022). It follows that either a large part of those patents does not translate into capital goods, or, more likely, that the adoption of robots in the sector has started only recently due to: (a) the complexity of the necessary authorizations, and (b) the fact that pharmaceutical production lines are generally dedicated to a single product, making the use of multifunctional robots less interesting for the production activity[5].

---

[5] However, the possibility that IFR data do not cover all installed robots should also be considered. Certain sectors, such as health services, are strategic sectors with significant public funding. Since among strategic sectors (such as military-type robots) information is not provided, we cannot exclude that the same happens for the health sector.

Table 1 APR per industry and period (Delta robots per 100.000 employed)

	APR 2000–2004	APR 2004–2008	APR 2008–2012	APR 2012–2017
Agriculture, forestry, and fishing	.258	7.452	2.894	9.241
All services	.735	.337	.663	1.188
Basic metals, fabricated metal products, except machinery and equip.	37.566	372.666	191.422	351.759
Chemicals and pharmaceutical products	0	0	8.7	19.085
Computer, electronic, optical products; electrical equipment	76.282	–49.451	226.734	100.670
Construction	.294	6.896	5.844	5.289
Food products, beverages, and tobacco	64.304	199.449	203.547	271.072
Machinery and equipment n.e.c.	–205.370	250.491	257.019	331.550
Mining and Utilities	2.06	8.388	5.66	8.188
Other manufacturing	16.573	–28.163	45.099	81.716
Other non-metallic mineral products	70.931	112.58	66.065	16.823
Paper products - Printing and reproduction of recorded media	13.008	32.942	41.197	75.433
Rubber and plastics products	230.875	1280.312	857.030	608.740
Textiles, wearing apparel, leather	–.370	–5.499	14.595	14.869
Transport equipment	1112.362	715.671	1155.101	638.528
Wood and products of wood and cork, except furniture	–3.387	40.403	–108.305	84.716

3.2 Regional exposure to robotization (EXP)

Following Acemoglu and Restrepo (2020), sectoral APR is combined with the employment shares of different sectors and regions to calculate a proxy for regional exposure to robotization (EXP):

$$EXP_r = \sum_{i \in I} l_{r,i} \times APR_i \tag{3}$$

where $l_{r,i}$ are the employment shares of industry i in region r. Acemoglu and Restrepo (2020) define this measure of exposure to robotization as "constructed from the interaction between baseline industry shares in a local labor market and technological possibilities for the introduction of robots across industries" (p. 3).

To compute the regional employment shares for the sectors reported in Table 1, we first used the OECD Regional database to compute the shares of agriculture, construction, mining and utilities, services, and manufacturing, and then we reconstructed the shares of the different manufacturing sectors using Eurostat's Structural Business Statistic (SBS) database.

It is important to note that the first database (OECD regional) contains data for all employed workers (self-employed and employees) while the second (SBS) only reports data for employees. Despite this limitation, the resulting shares can be considered a good approximation of the sectoral composition of regional economies.

As the spatial classification between Eurostat and the OECD is not uniform due to the repeated spatial variations over the last 20 years, and to the fact that, in some cases, the OECD considers larger regional partitions than Eurostat, regions have been aggregated at the level of the OECD classification. Moreover, given the impossibility of obtaining available data at the NUTS 2 level for Ireland and Finland, we consider Ireland at the national level and only two regions for Finland. In addition, overseas regions were excluded from the analysis. Finally, economic sectors (particularly manufacturing sectors) were translated from NACE Rev. 1.1 to NACE Rev. 2 and then aggregated according to the nomenclature proposed by IFR. For more detail about the aggregation methods used for territorial and sectoral breakdowns, see Compagnucci et al. (2021).

This process allowed us to calculate the Regional Exposure to Robotization (EXP) of the EURO area regions using the number of robots installed in the 16 industrial sectors reported in Table 1. It shows that the only relevant sector for which no analysis could be provided is "Coke and refined petroleum products" due to the lack or limited availability of related employment data at the regional level.

As data on robotization at the regional level are not available, EXP should be considered as a proxy of the potential exposure to robotization, or, in other words, the theoretical risk to which workers are exposed, based on the sectoral composition of the regional economy and the installations of robots (considered at the European level) in different sectors.

The measures of EXP in the four periods are reported in Fig. 1. Again, it is useful to emphasize some stylized facts. First, it is worth remembering that the different sectors contribute to EXP according to the amplitude of the sectoral APR and the importance of the different economic sectors at the regional level. It follows that the
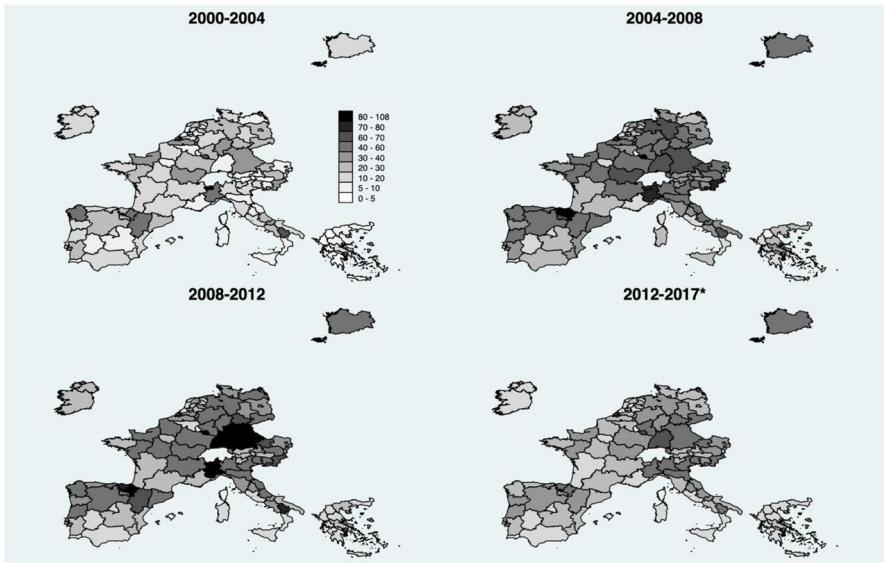
Fig. 1 Regional exposure to robotization (delta robots per 100,000 employed). Source: authors' original calculations on IFR, STAN and SBS data. N.B.: In this case, the last period has been weighted by 4/5 to take into account the longer time interval. N.B.2: In the maps "PT20" "PT30", and "ES70", i.e., the furthest island, have been removed for the sake of clarity. They are, however, included in the analysis

most exposed regions are those more specialized in the production of "Rubber and plastic products" and "Transport equipment". The EXP, in fact, is greater in Germany, in northern Italy, in the Spanish Atlantic area, and in various regions of France. For the same reason, Basilicata is the only region in southern Italy to be highly exposed, given the presence of several companies related to the automotive industry.

Secondly, it should be noted that, after the 2008 financial crisis, there has been a surge in EXP in every region. According to the equations used for APR (1) and EXP (2), this is not a consequence of an increase in robot installations, but rather of a negative output growth rate.

4 Strategy of analysis and econometric models

The second step of the analysis consists of estimating different models, starting from the following generic panel specification:

$$\Delta Y_i^{t,t-1} = \mu_i + \gamma_t + \beta_0 \cdot EXP_i^{t,t-1} + \beta_1 \cdot \text{INT\_DUMMY} \cdot EXP_i^{t,t-1} + \sum_{c=1}^{C} \theta_c \cdot Control_{i;t-1}^c +$$
$$+ \rho \cdot \sum_{j=1}^{n} w_{i,j} \cdot \Delta Y_j^{t,t-1} + v_{i,t}$$
$$v_{i,t} = \lambda \cdot \sum_{j=1}^{n} w_{i,j} \cdot v_{j,t} + \epsilon_{i,t}$$

where:

– $\Delta Y_i^{t,t-1}$ is the variation in the dependent variable which, depending on the case, coincides with:

Table 2 Summary statistics for stacked differences panel

	Mean	Std. Dev.	N
Exposure to robotization ("delta" robots per hundred thousand employed)	28.97	19.09	460
Household income per-capita growth rate (national currency, constant price)	1.1	8.1	460
Δ Employment rate	.802	3.81	454
Δ Unemployment rate	.567	4.739	443
Δ Labour force participation rate	1.269	1.966	456
Labor utilization (number of weekly hours worked per capita, growth rate)	.22	11.67	460
GDP per-capita growth rate (national currency, constant price)	2.5	8.0	460
Services emp. Share	72.1	8.5	460
Manufacturing emp. Share	13.0	6.0	460
Agriculture emp. Share	6.2	6.1	460
Construction emp. Share	7.3	2.2	460
Mining and utilities emp. Share	1.4	0.9	460
Population density (pop. per m^2)	350	857	460
Share of elderly population (%, 65+)	18.9	3.3	460
Sex ratio (% population males over females)	96.1	2.7	460
PCT patent applications per thousand inhabitants	81	103	460

1. the households' income per-capita growth rate (constant prices)[6].
2. the variation in the employment rate.
3. the variation in the unemployment rate.
4. the variation in the labor force participation rate.
5. the labor utilization (worked hours/population) growth rate.

– All the dependent variables are considered in four periods using a stacked differences panel analysis (hence t = 2000, 2004, 2008, 2012, 2017). As the last period is longer than the others, its changes (ΔY and EXP) are weighted by 4/5 (the same applies to Table 2).
– μ_i e γ_t are the regional and time fixed effects, respectively.
– EXP is our variable of interest, which interacts in the different models considered with two different dummies (INT_DUMMY) that distinguish between: (1) regions with a high level of investment in R&D (HIGH_R&D = 1) and the others (HIGH_R&D = 0); (2) regions with a highly educated workforce (HIGH_EDU = 1) and the others (HIGH_EDU = 0). In the case of R&D expenditure, we compute the yearly median for each region over the entire 2000–2017 period. Each of them is successively compared with the overall median. When the regional median is higher than the overall median, than we assign the value 1 to the relative dummy, otherwise the assigned

---

[6] For income per capita and labor utilization, we use the growth rate instead of the variation of the rate for a sake of comparison with related literature. Acemoglu and Restrepo (2020), for example, use the variation when the dependent variable is a rate (i.e., employment) and the growth rate when the dependent variable is the wage (in line with our 'household income') or the quantity of labor (in line with our 'labor utilization').

value is 0. The same applies to the percentage of the population (between 25 and 64 years) with at least an upper secondary education level and the corresponding dummy related to the level of education. By estimating β_0, we obtain the coefficient measuring the correlation of EXP with the dependent variable for the regions with dummy equal to 0, while β_1 regards the difference between the coefficient of the regions with dummy equal to 0 and those with dummy equal to 1. The sum of the two coefficients explains the overall effect of robotization risk in the regions with dummy equal to 1.

– *Control* are the regional controls. Specifically: GDP per-capita growth rate (which allows us to control for the economic cycle); employment shares in manufacturing, utilities and mining, agriculture, construction (which allows us to split the exposition to robotization per se from the mere industrial composition – services are the omitted reference sector); number of patents; population density; percentage of population over 65; male–female ratio. Except for the GDP growth rate, all variables' values are considered at t_0.

– Finally, ρ is the spatial correlation of the dependent variable, and λ the spatial correlation of the errors. By estimating these parameters, we further check the robustness of the results with respect to potential spatial autocorrelation bias. In particular, the models without ρ e λ are normal fixed-effects panels; models with $\rho \neq 0$ and $\lambda = 0$ are labeled as SAR (spatial autoregressive model); models with $\rho \neq 0$ and $\lambda \neq 0$ are labeled as SAC (spatial autoregressive combined model); models with $\rho = 0$ and $\lambda \neq 0$ are labeled as SEM (spatial error model) (Lee and Yu 2010; Belotti et al. 2017).

Table 2 shows the descriptive statistics of the variables used in the analysis. All the variables other than "exposure to robotization" come from the OECD Regional database[7]. The trends of the five dependent variables considered in the four periods are reported in Appendix (Figs. 3, 4, 5, 6 and 7).

To proxy the role of policies, and being aware that we are simplifying the issue, we interact the regional exposure to robotization with a dummy taking the value of 1 for regions above the median[8] in: (1) the level of investment in R&D, as a percentage of GDP; and (2) the level of education, as a percentage of the population between 25 and 64 years old with at least an upper secondary education level[9].

---

[7] Only in the case of "population density" we had to interpolate missing data (a maximum of three out of 19 years for most regions, except for the Região Autónoma dos Açores (PT), which shows 14 missing values.

[8] The level of education and R&D expenditure can be regarded as structural features of a national/regional economic system. As they produce positive externalities both for the private sector and, above all, for society at large, public policies can replace or incentivize private agents if their level of investment is not adequate. Although this support refers not only to regional policies but also to national ones, according to the peculiar institutional set-up of the EU countries, the final regional impact will still be heterogeneous, depending on the different absorptive capacity of each region. Finally, we use the median as a benchmark to distinguish as objectively as possible between regions investing relatively 'more' and those investing relatively 'less' in education and R&D, without assuming an a priori threshold. Obviously, individual regional/national policy makers cannot substantially change the value of the median.

[9] The upper secondary education was chosen because the technical colleges typical of the German educational system are classified as secondary education although they provide tertiary education in terms of applied and technical skills. Furthermore, unlike tertiary education, secondary one can be more likely affected by regional policy, as explained in the Introduction.
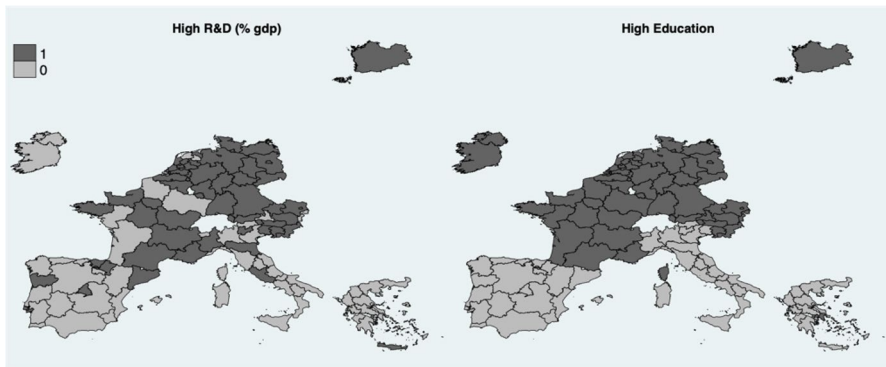
Fig. 2 Regional dummies for high R&D expenditure and high education workforce. Source: authors' original calculations on OECD Regional database and EUROSTAT database

The values of these dummies, and their respective classifications, are illustrated in Fig. 2. In this case, data for R&D expenditure and education level come from the OECD Regional database.

Figure 2 shows the existence of national patterns, which significantly affect regional characteristics and, consequently, related dummies. This is an expected result since national policies importantly influence R&D and education levels, even though a relevant difference can be noted. Specifically, as far as education is concerned, only national patterns arise: regions belonging to central and northern European countries show performances above the median, contrary to what happens in southern Europe. The same cannot be said unequivocally for R&D investment, since France, Spain, and Italy show some regional heterogeneity.

Finally, the fact that the two dummies differ in some, but relatively few, regions, suggests that similar results could be expected when using the two dummies in the regressions. For this very reason, however, the possible existence of differences in the estimation results can provide interesting insights about the relative role of the two policies.

5 Results

Tables 3, 4, 5, 6 and 7 report the outcome of the econometric analysis. Results are consistent regardless of the different variables and statistical technique used, confirming the different points of view reported in the theoretical section. Robotization negatively affects households' income growth, whereas results on employment, unemployment, labor force participation rate, and labor utilization are less unequivocal. Yet, what is crucial here is the relation between EXP and long-term policies.

Table 3 reports the results for all models. Specifically, it shows that the household disposable income growth rate (the dependent variable) is negatively correlated with EXP in the case of regions with a low level of investment in R&D. The regions with

Table 3 Stacked differences panel, Dep. Var: (real) household income per–capita growth rate

	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Reg. fixed effects	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
R&D interaction			✓		✓		✓
Main							
EXP	-0.0901**	-0.0753*	-0.0777**	-0.0612*	-0.0750**	-0.0688*	-0.0850**
	(0.0411)	(0.0384)	(0.0379)	(0.0371)	(0.0417)	(0.0363)	(0.0379)
EXP × High R&D	0.2230***	0.2099***	0.1014***	0.1812***	0.1097***	0.1873***	0.1132***
	(0.0446)	(0.0423)	(0.0324)	(0.0383)	(0.0318)	(0.0395)	(0.0317)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	-1.370	-1.466	-0.930	-1.649	-0.215	-1.677	-0.111
	(1.283)	(1.269)	(1.159)	(1.812)	(1.399)	(1.826)	(1.444)
2008–2012	-12.203***	-9.150***	-2.221	-12.216***	-3.613*	-14.890***	-6.067***
	(1.366)	(1.264)	(1.928)	(1.7440)	(1.974)	(1.868)	(2.023)
2012–2017	-2.663***	-2.288***	-1.810	-3.155**	-1.822	-3.656***	-2.436
	(0.884)	(0.848)	(2.184)	(1.341)	(2.047)	(1.389)	(2.085)
Spatial							
ρ		0.7998***	0.7659***	0.6548***	0.6483***		
		(0.0407)	(0.0569)	(0.1064)	(0.1033)		
λ				0.8771***	0.8325***	0.8951***	0.8616***
				(0.0343)	(0.0344)	(0.0234)	(0.0279)
Test							
EXP + EXP × High R&D	0.1328***	0.1346***	0.0237	0.1199***	0.0347	0.1184***	0.0282
	(0.0395)	(0.0382)	(0.0273)	(0.0359)	(0.0279)	(0.0363)	(0.0284)
r2_w	0.3891	0.2452	0.5319	0.3054	0.5323	0.3864	0.5811
r2_b	0.1296	0.1448	0.0058	0.1348	0.0016	0.1305	0.0528
N (n × t)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)

Table 3 (continued)

	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Education interaction							
Main							
EXP	-0.0818***	-0.0655*	-0.0751**	-0.0586	-0.0744**	-0.0683*	-0.0860***
	(0.0368)	(0.0352)	(0.0316)	(0.0358)	(0.0324)	(0.0362)	(0.0319)
EXP × High EDU	0.2665***	0.2470***	0.1283***	0.2244***	0.1423***	0.2361***	0.1505***
	(0.0372)	(0.0358)	(0.0286)	(0.0357)	(0.0299)	(0.0361)	(0.0293)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	-1.8982	-1.9605	-1.3194	-2.0229	-0.5894	-2.0580	-0.5038
	(1.2924)	(1.2846)	(1.1367)	(1.8325)	(1.3738)	(1.8456)	(1.4147)
2008–2012	-12.6714***	-9.6165***	-2.7436	-12.5992***	-4.1454**	-15.2120***	-6.5741***
	(1.3863)	(1.2819)	(1.9385)	(1.7606)	(1.9798)	(1.8918)	(2.0166)
2012–2017	-2.9501***	-2.5599***	-2.1433	-3.3755**	-2.1306	-3.8701***	-2.7387
	(0.9031)	(0.8681)	(2.2072)	(1.3768)	(2.0808)	(1.4281)	(2.1177)
Spatial							
ρ		0.7923***	0.7603***	0.6369***	0.6360***		
		(0.0436)	(0.0590)	(0.1143)	(0.1073)		
λ				0.8742***	0.8350***	0.8924***	0.8625***
				(0.0349)	(0.0344)	(0.0240)	(0.0281)
Test							
EXP + EXP × High EDU	0.1848***	0.1815***	0.0532*	0.1657***	0.0679**	0.1678***	0.0645**
	(0.0376)	(0.0369)	(0.0286)	(0.0339)	(0.0293)	(0.0339)	(0.0286)
r2_w	0.4011	0.2629	0.5382	0.3221	0.5381	0.3981	0.5850
r2_b	0.4208	0.4262	0.0036	0.4277	0.0001	0.4215	0.0985
N (n × t)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

Controls: GDP per-capita growth rate; Manufacturing emp. share, Agriculture emp. share; Construction emp. share; Mining and Utilities emp. share; Population density; Share of Elderly Pop. (%, 65+); Sex Ratio (% males over females); PCT patent applications per thousand inhabitants.

Table 4 Stacked differences panel, Dep. Var: Δ Employment rate

	Panel FE	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Reg. fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓			✓		✓	✓	✓
R&D interaction								
Main								
EXP	−0.0122 (0.0218)	−0.0205 (0.0181)	−0.0019 (0.0193)	−0.0123 (0.0183)	0.0016 (0.0183)	−0.0136 (0.0181)	0.0003 (0.0187)	−0.0142 (0.0182)
EXP × High R&D	0.1370*** (0.0274)	0.0717*** (0.0200)	0.1209*** (0.0248)	0.0661*** (0.0193)	0.1046*** (0.0245)	0.0670*** (0.0192)	0.1087*** (0.0250)	0.0680*** (0.0190)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	0.3776 (0.5424)	1.1781** (0.5810)	−0.4340 (0.4766)	0.5463 (0.5745)	−0.1865 (0.6420)	1.0265 (0.7442)	0.0362 (0.6558)	1.1228 (0.7243)
2008–2012	−5.3529*** (0.6962)	−2.2843** (0.8891)	−4.4322*** (0.6267)	−1.8663** (0.8575)	−6.0905*** (0.9909)	−3.0150*** (1.1580)	−6.7870*** (0.8521)	−3.2073*** (1.0562)
2012–2017	0.1436 (0.2949)	−0.4836 (0.9406)	−0.1950 (0.2726)	−0.6635 (0.9061)	0.1472 (0.4184)	−0.3007 (0.9645)	0.2454 (0.4226)	−0.2643 (0.9596)
Spatial								
ρ			0.8103*** (0.0313)	0.5461*** (0.1442)	0.4472 (0.3214)	0.1354 (0.3918)		
λ					0.8944*** (0.0265)	0.8000*** (0.0527)	0.9141*** (0.0155)	0.8231*** (0.0497)
Test								
EXP + EXP × High R&D	0.1248*** (0.0260)	0.0512** (0.0209)	0.1190*** (0.0236)	0.0538*** (0.0202)	0.1063*** (0.0224)	0.0534*** (0.0206)	0.1090*** (0.0228)	0.0537*** (0.0206)
r2_w	0.4380	0.6427	0.2768	0.6255	0.3805	0.6293	0.4262	0.6325
r2_b	0.1355	0.0648	0.2192	0.0178	0.1626	0.0643	0.1398	0.0868
N (n × t)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)

Table 4 (continued)

	Panel FE	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Education interaction								
Main								
EXP	-0.0192 (0.0199)	-0.0246 (0.0154)	-0.0084 (0.0173)	-0.0167 (0.0152)	-0.0094 (0.0169)	-0.0207 (0.0153)	-0.0114 (0.0174)	-0.0210 (0.0154)
EXP × High EDU	0.1881*** (0.0270)	0.1060*** (0.0224)	0.1667*** (0.0247)	0.0984*** (0.0217)	0.1558*** (0.0264)	0.1054*** (0.0233)	0.1617*** (0.0262)	0.1061*** (0.0223)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	0.0408 (0.5664)	0.8376 (0.5832)	-0.7054 (0.5045)	0.2750 (0.5791)	-0.3416 (0.6499)	0.7938 (0.7322)	-0.1717 (0.6566)	0.8306 (0.7090)
2008–2012	-5.6595*** (0.7026)	-2.7511*** (0.8997)	-4.7346*** (0.6345)	-2.3293*** (0.8660)	-6.4179*** (0.9936)	-3.5402*** (1.1475)	-6.9673*** (0.8307)	-3.6177*** (1.0416)
2012–2017	-0.0499 (0.3078)	-0.7851 (0.9256)	-0.3552 (0.2870)	-0.9305 (0.8936)	0.0366 (0.4330)	-0.5188 (0.9468)	0.1102 (0.4344)	-0.5054 (0.9390)
Spatial								
ρ			0.7833*** (0.0363)	0.5074*** (0.1368)	0.3490 (0.3415)	0.0539 (0.3740)		
λ					0.8917*** (0.0261)	0.8142*** (0.0478)	0.9079*** (0.0169)	0.8226*** (0.0479)
Test								
EXP + EXP × High EDU	0.1689*** (0.0317)	0.0814*** (0.0269)	0.1583*** (0.0291)	0.0817*** (0.0261)	0.1464*** (0.0288)	0.0847*** (0.0273)	0.1503*** (0.0288)	0.0850*** (0.0269)
r2_w	0.4761	0.6548	0.3384	0.6402	0.4318	0.6438	0.4635	0.6451
r2_b	0.1914	0.0887	0.2525	0.0044	0.2072	0.1104	0.1948	0.1182
N (n × t)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

Controls: GDP per capita growth rate; Manufacturing emp. share, Agriculture emp. share; Construction emp. share; Mining and Utilities emp. share; Population density; Share of Elderly Pop. (%, 65+); Sex Ratio (% males over females); PCT patent applications per thousand inhabitants.

Table 5 Stacked differences panel, Dep. Var: Δ labour force participation rate

	Panel FE	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Reg. fixed effects	✓			✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓		✓		✓
R&D interaction								
Main								
EXP	−0.0019 (0.0177)	−0.0063 (0.0176)	−0.0018 (0.0177)	−0.0065 (0.0172)	−0.0022 (0.0178)	−0.0053 (0.0176)	−0.0022 (0.0179)	−0.0044 (0.0176)
EXP × High R&D	0.0351* (0.0184)	0.0486** (0.0200)	0.0321* (0.0182)	0.0456** (0.0195)	0.0306* (0.0183)	0.0446** (0.0196)	0.0311* (0.0183)	0.0449** (0.0196)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	0.3123 (0.4056)	0.7592 (0.4718)	0.1369 (0.3970)	0.5452 (0.4528)	0.1836 (0.4586)	0.5537 (0.5006)	0.2770 (0.4966)	0.6435 (0.5516)
2008–2012	−0.8787** (0.3434)	0.1267 (0.5656)	−0.7616** (0.3409)	0.1653 (0.5547)	−0.8157** (0.3807)	0.0860 (0.6033)	−0.9228** (0.3992)	−0.0253 (0.6185)
2012–2017	−0.6809*** (0.2533)	1.0443* (0.5367)	−0.5626** (0.2510)	1.0549** (0.5226)	−0.6111** (0.2973)	1.0698** (0.5361)	−0.7036** (0.3232)	1.0523* (0.5508)
Spatial								
ρ			0.5672*** (0.1180)	0.5443*** (0.1345)	0.4128* (0.1633)	0.4027* (0.2101)		
λ				0.3962** (0.1493)	0.3151 (0.1677)	0.5848*** (0.0864)	0.5357*** (0.0841)	0.3962*** (0.1493)
Test								
EXP + EXP × High R&D	0.0332** (0.0142)	0.0423** (0.0185)	0.0303** (0.0136)	0.0391** (0.0176)	0.0283** (0.0139)	0.0393** (0.0179)	0.0289** (0.0140)	0.0405** (0.0182)
r2_w	0.0961	0.1647	0.0972	0.1599	0.0965	0.1611	0.0954	0.1629
r2_b	0.0096	0.0058	0.0115	0.0027	0.0107	0.0069	0.0095	0.0096
N (n × t)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)

Table 5 (continued)

	Panel FE	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Education interaction								
Main								
EXP	−0.0027 (0.0141)	−0.0024 (0.0147)	−0.0027 (0.0140)	−0.0030 (0.0143)	−0.0041 (0.0142)	−0.0027 (0.0147)	−0.0045 (0.0143)	−0.0023 (0.0149)
EXP × High EDU	0.0464*** (0.0173)	0.0569*** (0.0201)	0.0429** (0.0169)	0.0538*** (0.0194)	0.0428** (0.0174)	0.0543*** (0.0198)	0.0442** (0.0177)	0.0556*** (0.0202)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	0.2267 (0.4139)	0.5705 (0.4881)	0.0626 (0.4050)	0.3704 (0.4691)	0.1174 (0.4653)	0.3845 (0.5189)	0.2099 (0.4996)	0.4715 (0.5630)
2008–2012	−0.9559*** (0.3477)	−0.1200 (0.5826)	−0.8355** (0.3446)	−0.0686 (0.5715)	−0.8826** (0.3803)	−0.1489 (0.6150)	−0.9835** (0.3970)	−0.2504 (0.6275)
2012–2017	−0.7293*** (0.2566)	0.8651 (0.5502)	−0.6101** (0.2541)	0.8858* (0.5365)	−0.6554** (0.2982)	0.9115* (0.5503)	−0.7438** (0.3224)	0.8972 (0.5630)
Spatial								
ρ			0.5535*** (0.1197)	0.5354*** (0.1348)	0.3975** (0.1657)	0.3801* (0.2241)		
λ					0.3926*** (0.1430)	0.3394** (0.1420)	0.5744*** (0.0861)	0.5361*** (0.0753)
Test								
EXP + EXP × High EDU	0.0437** (0.0175)	0.0545** (0.0222)	0.0402** (0.0168)	0.0508** (0.0211)	0.0387** (0.0171)	0.0517** (0.0216)	0.0397** (0.0174)	0.0533** (0.0221)
r2_w	0.1053	0.1728	0.1061	0.1666	0.1057	0.1686	0.1048	0.1711
r2_b	0.0013	0.0046	0.0014	0.0015	0.0011	0.0055	0.0011	0.0081
N (n×1)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)	452 (113×4)

Robust standard errors in parentheses; $^{*} p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$;

Controls: GDP per-capita growth rate; Manufacturing emp. share, Agriculture emp. share; Construction emp. share; Mining and Utilities emp. share; Population density; Share of Elderly Pop. (%, 65+); Sex Ratio (% males over females); PCT patent applications per thousand inhabitants.

Table 6 Stacked differences panel, Dep. Var: Labor Utilisation (worked hours per capita) growth rate

	Panel FE	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Reg. fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
R&D interaction								
Main								
EXP	-0.0174	-0.0147	-0.0053	-0.0086	0.0129	0.0021	0.0118	0.0016
	(0.0711)	(0.0504)	(0.0717)	(0.0504)	(0.0681)	(0.0493)	(0.0677)	(0.0493)
EXP × High R&D	0.2431***	0.1680***	0.2281***	0.1633***	0.1979***	0.1590**	0.1998***	0.1599**
	(0.0636)	(0.0612)	(0.0651)	(0.0627)	(0.0663)	(0.0633)	(0.0657)	(0.0624)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	0.3330	0.6789	-0.4038	0.2829	-0.4601	0.3083	-0.3393	0.3910
	(2.3903)	(2.4816)	(2.7290)	(2.7329)	(3.1464)	(2.9405)	(3.0968)	(2.8504)
2008–2012	-12.3474***	-10.1008***	-11.1811***	-9.6602***	-13.6446***	-10.8446***	-14.1289***	-11.0528***
	(1.4102)	(2.0334)	(1.5208)	(2.0994)	(1.6598)	(2.1853)	(1.6599)	(2.0990)
2012–2017	-1.4388	-4.8374*	-1.5401*	-4.8736*	-1.7095	-4.7570*	-1.7228	-4.7491*
	(0.9044)	(2.6743)	(0.8912)	(2.6287)	(1.1186)	(2.7183)	(1.1370)	(2.7230)
Spatial								
ρ			0.3785	0.1792	0.1196	0.0556		
			(0.2355)	(0.1665)	(0.1334)	(0.1149)		
λ					0.6079***	0.3709***	0.6266***	0.3890**
					(0.1980)	(0.1383)	(0.2026)	(0.1627)
Test								
EXP + EXP × High R&D	0.2257***	0.1533***	0.2228***	0.1547***	0.2108***	0.1611***	0.2116***	0.1615***
	(0.0518)	(0.0515)	(0.0489)	(0.0492)	(0.0458)	(0.0512)	(0.0462)	(0.0510)
r2_w	0.2127	0.2578	0.2002	0.2564	0.2075	0.2561	0.2109	0.2566
r2_b	0.0082	0.0020	0.0099	0.0021	0.0086	0.0028	0.0081	0.0027
N (n × t)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)

Table 6 (continued)

	Panel FE	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Education interaction								
Main								
EXP	-0.0427 (0.0612)	-0.0325 (0.0435)	-0.0317 (0.0629)	-0.0276 (0.0431)	-0.0189 (0.0614)	-0.0192 (0.0426)	-0.0198 (0.0609)	-0.0193 (0.0425)
EXP × High EDU	0.3537*** (0.0541)	0.2601*** (0.0585)	0.3362*** (0.0580)	0.2549*** (0.0612)	0.3109*** (0.0619)	0.2535*** (0.0622)	0.3127*** (0.0609)	0.2539*** (0.0606)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	-0.2681 (2.3371)	-0.0786 (2.3397)	-0.8412 (2.6511)	-0.3590 (2.5578)	-0.7880 (2.9877)	-0.2945 (2.7328)	-0.7279 (2.9435)	-0.2758 (2.6382)
2008–2012	-12.9034*** (1.4073)	-11.1131*** (2.0168)	-11.9205*** (1.5706)	-10.7638*** (2.1161)	-14.1276*** (1.6300)	-11.8261*** (2.1624)	-14.3666*** (1.6131)	-11.8745*** (2.0575)
2012–2017	-1.7946** (0.9058)	-5.4177** (2.5698)	-1.8597** (0.8905)	-5.4327** (2.5264)	-1.9740* (1.1001)	-5.2581** (2.6164)	-1.9807* (1.1116)	-5.2561** (2.6138)
Spatial								
ρ			0.3099 (0.2343)	0.1338 (0.1574)	0.0583 (0.1098)	0.0127 (0.1030)		
λ					0.5652*** (0.2141)	0.3452** (0.1380)	0.5758*** (0.2193)	0.3496** (0.1539)
Test								
EXP + EXP × High EDU	0.3110*** (0.0557)	0.2276*** (0.0589)	0.3045*** (0.0525)	0.2273*** (0.0574)	0.2920*** (0.0499)	0.2343*** (0.0593)	0.2929*** (0.0502)	0.2346*** (0.0585)
r2_w	0.2288	0.2663	0.2202	0.2653	0.2257	0.2653	0.2272	0.2654
r2_b	0.0470	0.0125	0.0474	0.0135	0.0464	0.0154	0.0463	0.0153
N (n × t)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)	460 (115×4)

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

Controls: GDP per capita growth rate; Manufacturing emp. share; Agriculture emp. share; Construction emp. share; Mining and Utilities emp. share; Population density; Share of Elderly Pop. (%, 65+); Sex Ratio (% males over females); PCT patent applications per thousand inhabitants.

Table 7 Stacked differences panel, Dep. Var: Δ unemployment rate

	Panel FE	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Reg. fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓		✓		✓		✓
R&D interaction								
Main								
EXP	0.0184	0.0237	0.0042	0.0122	-0.0061	0.0187	-0.0031	0.0204
	(0.0302)	(0.0203)	(0.0249)	(0.0204)	(0.0224)	(0.0209)	(0.0238)	(0.0196)
EXP × High R&D	-0.1522***	-0.0414**	-0.1349***	-0.0375**	-0.1121***	-0.0366**	-0.1195***	-0.0365**
	(0.0318)	(0.0189)	(0.0278)	(0.0182)	(0.0252)	(0.0171)	(0.0273)	(0.0171)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	-0.0215	-0.2302	0.7894	0.3614	0.6485	-0.4274	0.3589	-0.5611
	(0.6111)	(0.5553)	(0.5147)	(0.5410)	(0.6700)	(0.6072)	(0.6883)	(0.5762)
2008–2012	6.6756***	4.0967***	5.4684***	3.4919***	7.3334***	2.9475***	8.7880***	2.9380***
	(0.8958)	(1.1239)	(0.7982)	(1.0682)	(1.0969)	(0.9086)	(1.1073)	(0.9049)
2012–2017	-0.7584*	2.8597*	-0.1178	3.0863***	-0.5391	2.4666***	-0.8521	2.4384***
	(0.4222)	(1.1091)	(0.3731)	(1.0725)	(0.6102)	(0.8650)	(0.6254)	(0.8662)
Spatial								
ρ			0.8510***	0.5648***	0.7396***	0.0430		
			(0.0186)	(0.1676)	(0.0742)	(0.1303)		
λ					0.9207***	3.6572***	0.9317***	3.6525***
					(0.0159)	(0.1553)	(0.0085)	(0.1519)
Test								
EXP + EXP × High R&D	-0.1339***	-0.0177	-0.1307***	-0.0253*	-0.1182***	-0.0179	-0.1226***	-0.0161
	(0.0281)	(0.0144)	(0.0250)	(0.0149)	(0.0226)	(0.0151)	(0.0239)	(0.0137)
r2_w	0.4272	0.7237	0.2099	0.6971	0.2836	0.6943	0.4193	0.6947
r2_b	0.1722	0.1299	0.2970	0.0125	0.2554	0.1226	0.1816	0.1266
N (n × t)	432 (108×4)	432 (108×4)	432 (108×4)	432 (108×4)	432 (108×4)	432 (108×4)	432 (108×4)	432 (108×4)

Table 7 (continued)

	Panel FE	Panel FE SAR	Panel FE SAR	Panel FE SAC	Panel FE SAC	Panel FE SEM	Panel FE SEM
Education interaction							
Main							
EXP	0.0238 (0.0269)	0.0083 (0.0224)	0.0178 (0.0171)	0.0013 (0.0210)	0.0188 (0.0169)	0.0066 (0.0224)	0.0284 (0.0186)
EXP × High EDU	-0.2048*** (0.0288)	-0.0700*** (0.0191)	-0.0631*** (0.0184)	-0.1574*** (0.0250)	-0.0664*** (0.0184)	-0.1712*** (0.0267)	-0.0622*** (0.0198)
2000–2004	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2004–2008	0.3261 (0.6222)	1.0851** (0.5346)	0.5258 (0.5364)	0.8122 (0.6810)	0.0530 (0.6463)	0.5415 (0.6999)	-0.3703 (0.5726)
2008–2012	4.4091*** (1.1419)	5.7732*** (0.8012)	3.7958*** (1.0833)	7.5551*** (1.0871)	4.7804*** (1.3216)	8.9589*** (1.0934)	3.1925*** (0.9033)
2012–2017	3.0258*** (1.1048)	0.0442 (0.3743)	3.2280*** (1.0691)	-0.4429 (0.6200)	2.9757*** (1.0995)	-0.7363 (0.6340)	2.6048*** (0.8687)
Spatial							
ρ		0.8387*** (0.0214)	0.5437*** (0.1649)	0.7086*** (0.0874)	0.5010** (0.2240)		
λ				0.9176*** (0.0166)	0.8637*** (0.0307)	0.9286*** (0.0088)	3.6370*** (0.1620)
Test							
EXP + EXP × High EDU	-0.1810*** (0.0313)	-0.1717*** (0.0284)	-0.0453** (0.0184)	-0.1561*** (0.0262)	-0.0476*** (0.0183)	-0.1646*** (0.0274)	-0.0338* (0.0161)
r2_w	0.4560	0.2518	0.7041	0.3241	0.6883	0.4463	0.7008
r2_b	0.3033	0.4004	0.0033	0.3854	0.0000	0.3136	0.1424
N (n × t)	432 (108×4)	432 (108×4)	432 (108×4)	432 (108×4)	432 (108×4)	432 (108×4)	432 (108×4)

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

Controls: GDP per-capita growth rate; Manufacturing emp. share, Agriculture emp. share; Construction emp. share; Mining and Utilities emp. share; Population density; Share of Elderly Pop. (%, 65+); Sex Ratio (% males over females); PCT patent applications per thousand inhabitants.

high levels of investment in R&D show a better effect of EXP on the dependent variable with respect to the effect it exerts on the dependent variable of the region that invest less in R&D. However, this positive difference is not sufficient to cause an overall positive correlation between EXP and the household disposable income growth rate, and neither in the region with a high level of investment in R&D. In the empirical specification with controls, the overall coefficient of regions with a high level of expenditure in R&D (EXP+EXP * HIGH R&D) is never significantly different from zero.

Similarly, the results in the second part of the table, concerning the interaction between EXP and the educational level of the workforce (HIGH EDU), highlight how regions with lower levels of education suffer from a reduction in households' disposable income growth rate, while those with higher levels of education experience better results. In the case of HIGH EDU, the overall correlation (sum of coefficients) is positive for regions with a higher share of educated labor force.

The education level appears to be more important than the R&D expenditure since the difference between regions with high and low level of education is more relevant (the coefficient of EXP * HIGH EDU is larger than the coefficient of EXP * HIGH R&D) and the overall coefficient (EXP+EXP * HIGH R&D) is significantly larger than zero in models that take into account controls and spatial correlation.

Table 4 shows the results for all models considering the employment rate as the dependent variable. In this case, EXP is not negatively correlated with the variation in the employment rate of regions with low levels of investment in R&D nor with a low level of educated workforce. The correlation between EXP and the variation in the employment rate is positive and significant in the regions with a higher propensity to invest in R&D and which have well-trained workforce, to the point that the overall correlation is always positive and significant (EXP+EXP * HIGH R&D and EXP+EXP * HIGH EDU significantly greater than zero). Again, the parameters related to differences in education level are larger than those related to R&D expenditure.

The results of Table 5, concerning the variation in the labor force participation rate, and Table 6, regarding the variation in the labor utilization, *mutatis mutandis,* are totally comparable to those concerning the employment rate (Table 4). Again, the parameters related to differences in education are larger than those related to R&D expenditure.

Finally, Table 7 suggests identical considerations about the correlation between EXP and variation in the unemployment rate due to variation in R&D expenditure and education level (with inverted signs). In general, the parameters introduced to control for possible spatial correlations (r and l) turn out to be significantly different from zero, confirming the appropriateness of the analysis when controlling for these aspects. Finally, the homogeneity of the results among the different model specifications supports the soundness of our methodology and results.

The correlation between EXP and the different dependent variables, focusing on the sole models with control, is summarized in Table 8[10]. Four main stylized

---

[10] For each dependent variable, the table shows the signs of the correlations between the dependent variable and EXP (also interacted), which are always concordant in the four models with all controls (in each table, thus for each dependent variable).

Table 8 Correlation between regional EXP and variables under analysis (models with controls)

	Household Income growth rate	Δ Employment rate	Δ Activity rate	Labour utilization growth rate	Δ Unemployment rate
Low R&D	-	0	0	0	0
Difference High R&D/Low R&D	+	+	+	+	-
High R&D	0	+	+	+	0
Low EDU	-	0	0	0	0
Difference High EDU/Low EDU	+	+	+	+	-
High EDU	+	+	+	+	-

facts can be outlined. First, in the regions that invest more in R&D, we find a positive correlation between EXP and labor utilization, but not with the income growth rate, meaning that employees work more for the same overall wage. Secondly, in the regions with a higher level of educated citizens, we find a positive correlation between EXP both with labor utilization and income growth rate, meaning that employees work more for a higher overall wage. Thirdly, among these two patterns, that related to education and training appears to be more capable to cope with the effects of robotization, as proven by the higher value of the estimated coefficients and the positive association not only with the quantity of labor (as in the case of R&D), but also with income growth rate. Finally, all the variables considered are significantly associated with the difference between regions both with high and low level of education and R&D. Pushing such a result forward, we may argue that, in the lack of policy interventions, the distance between regions which invest more in education/R&D and those which invest less will increase as robotization expands.

Our results support the idea that more than a dichotomic positive or negative effect of robotization on employment and wages, we witness asymmetric outcomes depending on the relationship between the socioeconomic structure of a region and the policy implemented at its level. There may exist a complementarity effect between humans and robots as stated by many scholars. Nonetheless, the complementarity drawback may be improved by education and R&D policies, and by the subsequent positive social externalities they trigger. On the contrary, an increase of EXP in countries with low levels of R&D investment and education may amplify the negative consequences in terms of household income in the face of a stable trend of labor (employment rate, labor force participation rate, labor utilization) and unemployment rate. This means that the assumption of Pigou (1933 – point 4 of the positivist view), who argues that maintaining employment is possible by lowering wages, may be underway. However, this assumption, like all the others falling into the positivist view, basically focuses on the sole overall employment trend, regardless of the actual improvement in economic wellbeing at the individual and aggregate levels. Finally, results appear to confirm the polarizing nature of disruptive innovation, like robotization, which has been stressed by some authors, but which deserves more attention.

6 Conclusion

The current robotization process has renewed the long-lasting debate between techno-optimists and techno-pessimists about its effects on employment, and, ultimately, on citizens' wellbeing.

Against this background, the main contribution of our work is to empirically show that this impact can be both positive and negative, and that this heterogeneity is correlated with the implementation and the effects of long run policies (such as, but not only, R&D and education). In so doing, we contribute to fill the gap between the theoretical foundations of such an approach and the related (but currently scarce) empirical evidence. Furthermore, by focusing on the regional dimension, we cope with the scarcity of analyses at this territorial level mainly due to the lack of data. Implementing the Acemoglu and Restrepo (2020) methodology to compute the Regional Exposition to Robotization in 150 NUTS-2 regions of the Euro area, we show that the related risk in terms of employment losses is negatively correlated with higher levels of regional investment in R&D and education. In other terms, regions that invest more in R&D and education are more able to cope with the risks related to robotization. This result supports the idea that high levels of R&D and education trigger positive socioeconomic externalities, which allow to exploit the complementarity effect with machines while mitigating the negative outcomes of the substitution effect. Since the levels of investment in R&D and of citizens' education are importantly affected by public policies, one of the main issues to deal with regards the role of public intervention. Public policies must face the negative externalities arising in those regions with a suboptimal level of investment in R&D and education (which usually also suffer from poor economic performances) through direct intervention (public spending) and indirect intervention (incentives and subsidies to economic agents), especially in the absence of European solidarity mechanisms. Results appear to confirm the necessity of targeted R&D and education policies to avoid that robotization could further the ongoing polarization process triggered by technological advance.

This issue has become crucial given the importance that regional and local levels of government have gained in recent decades, especially with regard to cohesion policies. Especially after the 2008 financial crisis, the divergence between European regions has widened, undermining the credibility of the European project. Such an increase in divergence can be attributed to both institutional factors, such as the austerity policies which have been implemented in Greece, Italy, and Spain (Perez and Matsaganis 2018), and economic ones, such as the structural change which has occurred in the last two decades. Although robotization has exerted a crucial role in boosting structural change, our results suggest it cannot be considered as the only cause of the increase in income and territorial polarization. Other factors should be tested in further research, some of which are strictly related to the institutional level, pertaining, for instance, to the reduced role of the states in the economy, the flexibilization of the labor market, and the decreasing capacity of policy makers to implement redistribution policies.

Finally, despite the focus on European regions, our results clearly underline the role of national policies. Education, in particular, which seems to be more able than R&D to turn into positive the effects of robotization, responds to national patterns. One of its main drawbacks, though, is that education policies usually produce positive effects in a longer time than R&D policies. This finally calls for the joint implementation of both of these policies.
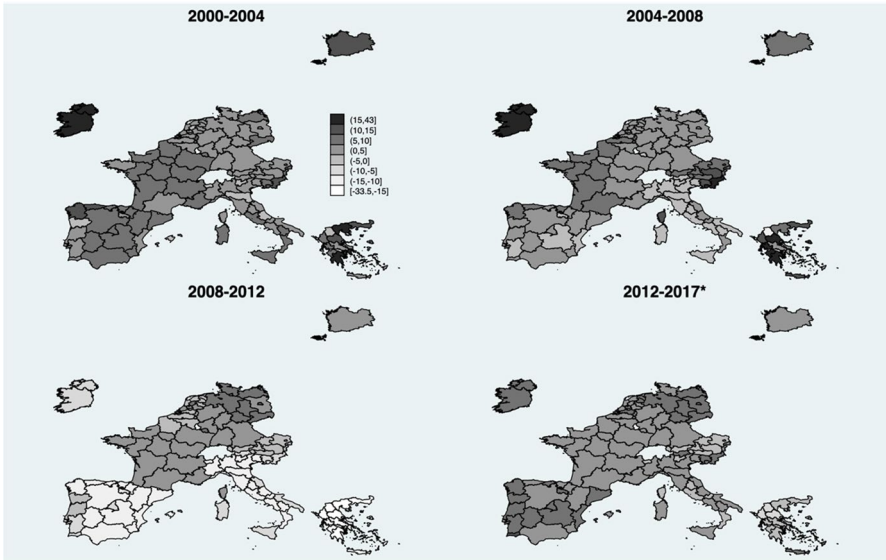
Appendix

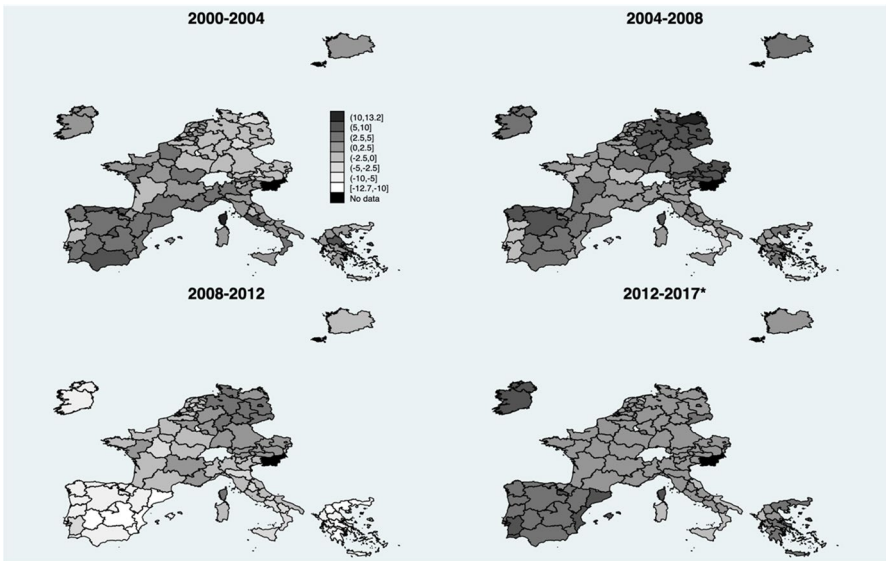**Fig. 3** Households' income per-capita growth rate, by period

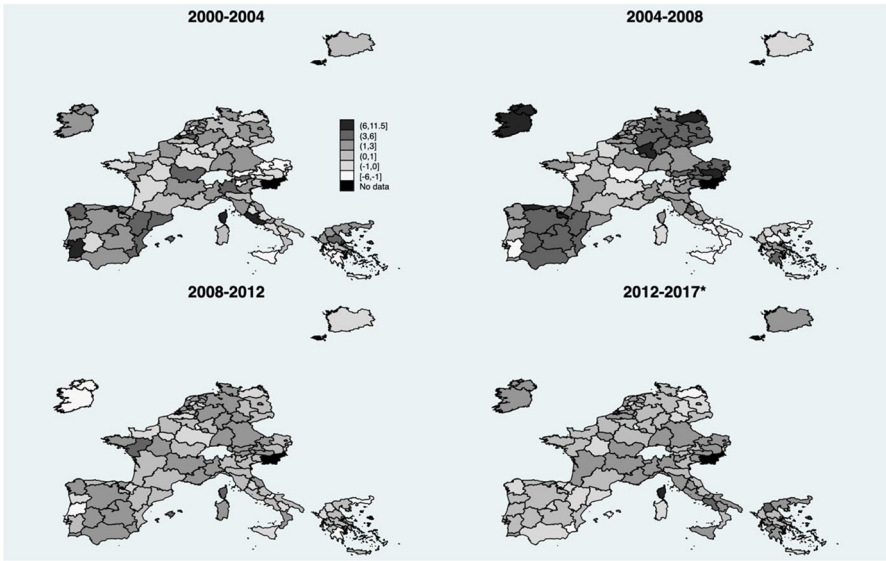**Fig. 4** Variation in the employment rate, by period

Fig. 5 Variation in the labour force participation rate, by period
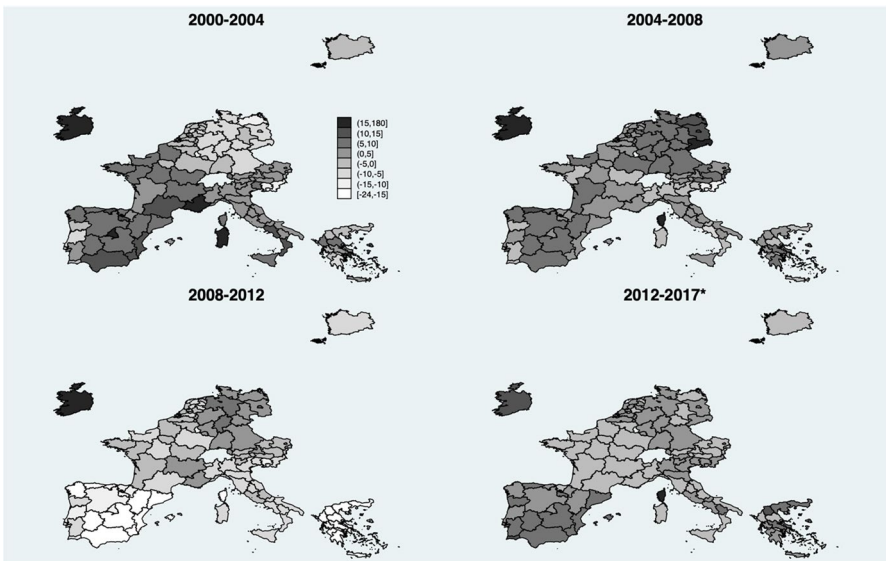

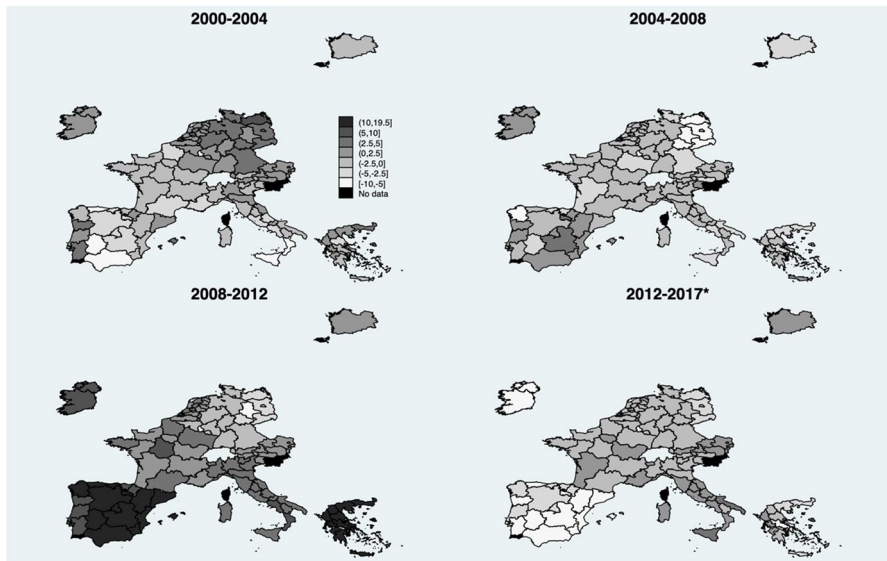**Fig. 6** Labor utilization (worked hours per capita) growth rate, by period

Fig. 7 Variation in the unemployment rate, by period

Declarations

References

Acemoglu D (1999) Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence. American Economic Review 89(5):1259–1278. https://doi.org/10.1257/aer.89.5.1259

Acemoglu D, Atkinson AB, Stiglitz JE (2015) Localised and biased technologies: Atkinson and Stiglitz's new view, induced innovations, and directed technological change. The Economic Journal 125(583):443–463. https://doi.org/10.1111/ecoj.12227

Acemoglu D, Autor D (2011) Skills, Tasks and Technologies: Implications for Employment and Earnings. In: Card D, Ashenfelter O (eds) Handbook of Labor Economics 4(b). Elsevier, North-Holland, pp 773–1823

Acemoglu D, Loebbing J (2022) Automation and Polarization. NBER Working Paper 30528. https://doi.org/10.3386/w30528

Acemoglu D, Restrepo P (2018) The race between man and machine: implications of technology for growth, factor shares, and employment. American Economic Review 108:1488–1542. https://doi.org/10.1257/aer.20160696

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

Acemoglu D, Restrepo P (2021) Tasks, Automation, and the Rise in US Wage Inequality. NBER Working Paper 28920. https://doi.org/10.3386/w28920

Aghion P, Antonin C, Bunel S (2019) Artificial Intelligence, Growth and Employment: The Role of Policy. Economie et Statistique/Economics and Statistics. https://hal-sciencespo.archives-ouvertes.fr/hal-03403370. Accessed 26 November 2021

Aldieri L, Makkonen T, Vinci CP (2021) Spoils of innovation? Employment effects of R&D and knowledge spillovers in Finland. Economics of innovation and new technology 30(4):356–370. https://doi.org/10.1080/10438599.2019.1703754

Alvaredo F, Chance L, Piketty T, Saez E, Zucman G (2017) Global Inequality Dynamics: New Findings From WID. World. American Economic Review 107(5):404–409. https://doi.org/10.1257/aer.p20171095

Andrews D, Criscuolo C, Gal PN (2016) The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy. OECD Productivity Working Papers 05. https://doi.org/10.1787/63629cc9-en

Arntz M, Gregory T, Zierahn U (2016) The risk of automation for jobs in OECD countries: a comparative analysis. OECD Social, Employment and Migration Working Papers 189. https://doi.org/10.1787/1815199X

Arrow KJ (1972) Economic Welfare and the Allocation of Resources for Invention. In: Rowley CK (ed) Readings in Industrial Economics. Palgrave, London. https://doi.org/10.1007/978-1-349-15486-9_13

Atkinson A, Stiglitz J (1969) A New View of Technological Change. Economic Journal 79(315):573–578. https://doi.org/10.2307/2230384

Attinasi M G, De Stefani R, Frohm E, Gunnella V, Koester, G., Tóth M, Melemenidis A (2021) The semiconductor shortage and its implication for euro area trade, production and prices. Economic Bulletin Boxes, 4. https://www.ecb.europa.eu/pub/economic-bulletin/focus/2021/html/ecb.ebbox202104_06~780de2a8fb.en.html. Accessed 13 November 2021

Autor DH, Katz LF, Krueger AB (1998) Computing inequality: have computers changed the labor market? The Quarterly journal of economics 113(4):1169–1213. https://doi.org/10.1162/003355398555874

Autor DH, Levy F, Murnane RJ (2003) The Skill Content of Recent Technological Change: An Empirical Exploration. Quarterly Journal of Economics 118(4):1279–1333. https://doi.org/10.1162/003355303322552801

Ballestar MT, Díaz-Chao Á, Sainz J, Torrent-Sellens J (2020) Knowledge, robots and productivity in SMEs: Explaining the second digital wave. Journal of Business Research 108:119–131. https://doi.org/10.1016/j.jbusres.2019.11.017

Baum-Snow N, Pavan R (2012) Understanding the City Size Wage Gap. The Review of Economic Studies 79(1):88–127. https://doi.org/10.1093/restud/rdr022

Belloc F, Burdin G, Landini F (2020) Robots and Worker Voice: An Empirical Exploration. IZA Discussion Paper Series 13799. https://www.iza.org/publications/dp/13799/robots-and-worker-voice-an-empirical-exploration. Accessed 30 October 2021

Belotti F, Hughes G, Piano Mortari A (2017) Spatial panel-data models using Stata. The Stata Journal 17(1):139–180. https://doi.org/10.1177/1536867X1701700109

Bessen J (2019) Automation and jobs: When technology boosts employment. Economic Policy 34(100):589–626. https://doi.org/10.1093/epolic/eiaa001

Bogliacino F, Piva M, Vivarelli M (2012) R&D and employment: An application of the of the LSDVC estimator using European microdata. Economics Letters 116(1):56–59. https://doi.org/10.1016/j.econlet.2012.01.010

Bruno G, Cavola M, Diglio A, Piccolo C (2022) Geographical accessibility to upper secondary education: an Italian regional case study. Ann Reg Sci 69:511–536. https://doi.org/10.1007/s00168-022-01146-6

Brynjolfsson E, Mcafee A (2011) Race against the machines: How the digital revolution is accelerating innovation, driving productivity and irreversibly transforming employment and the economy. Digital Frontier Press, Lexington

Brynjolfsson E, McAfee A (2014) The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company, New York

Cardamone P, Pupo V, Ricotta F (2018) Exploring the relationship between university and innovation: evidence from the Italian food industry. International Review of Applied Economics 32(5):673–696. https://doi.org/10.1080/02692171.2017.1357681

Caselli M, Fracasso A, Scicchitano S, Traverso S, Tundis E (2021) Stop worrying and love the robot: An activity-based approach to assess the impact of robotization on employment dynamics. GLO Discussion Paper 802. https://oa.inapp.org/xmlui/handle/20.500.12916/896. Accessed 1 December 2021

Ciarli T, Marzucchi A, Salgado E, Savona M (2018) The Effect of R&D Growth on Employment and Self-Employment in Local Labour Markets. SPRU Working Paper Series 08. https://doi.org/10.2139/ssrn.3147861

Cirillo V, Guarascio D (2015) Jobs and competitiveness in a polarised Europe. Intereconomics 50(3):156–160. https://doi.org/10.1007/s10272-015-0536-0

Compagnucci F, Gentili A, Valentini E, Gallegati M (2021) Have jobs and wages stopped rising? Productivity and structural change in advanced countries. Structural Change and Economic Dynamics 56(C):412–430. https://doi.org/10.1016/j.strueco.2018.07.003

Compagnucci F, Gentili A, Valentini E, Gallegati M (2022) Asymmetric responses to shocks: the role of structural change on resilience of the Euro area regions. Applied Economics 54(37):4324–4355. https://doi.org/10.1080/00036846.2022.2030045

Cséfalvay Z (2019) What are the policy options? A systematic review of policy responses to the impacts of robotisation and automation on the labour market. JRC Working Papers on Corporate R&D and Innovation 02/2019. https://www.econstor.eu/bitstream/10419/202183/1/jrc-wp201902.pdf. Accessed 29 October 2021

Dauth W, Findeisen S, Suedekum J, Woessner N (2019) The adjustment of labor markets to robots. Journal of the European Economic Association 19(6):3104–3153. https://doi.org/10.1093/jeea/jvab012

della Porta D, Keating M, Pianta M (2021) Inequalities, territorial politics, nationalism. Territory, Politics, Governance 9(3):325–330. https://doi.org/10.1080/21622671.2021.1918575

Delli Gatti D, Gallegati M, Greenwald BC, Russo A, Stiglitz JE (2012) Mobility constraints, productivity trends, and extended crises. Journal of Economic Behavior & Organization 83:375–393. https://doi.org/10.1016/j.jebo.2012.03.011

Engelbrecht HJ (1997) International R&D spillovers, human capital and productivity in OECD economies: An empirical investigation. European Economic Review 41(8):1479–1488. https://doi.org/10.1016/S0014-2921(96)00046-3

European Commission (2010) Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions, Europe 2020 Flagship Initiative Innovation Union, SEC(2010) 1161. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A52010DC0546. Accessed 20 Nov 2021

Fernald J (2014) Productivity and Potential Output Before, During, and After the Great Recession. NBER Macroeconomics Annual 29. https://doi.org/10.3386/w20248

Fleisher B, Li H, Zhao MQ (2010) Human capital, economic growth, and regional inequality in China. Journal of development economics 92(2):215–231. https://doi.org/10.1016/j.jdeveco.2009.01.010

Florida R (2002) The economic geography of talent. Annals of the Association of American Geographers 92(4):743–755. https://doi.org/10.1111/1467-8306.00314

Fratesi U, Perucca G (2019) EU regional development policy and territorial capital: A systemic approach. Papers in Regional Science 98(1):265–281. https://doi.org/10.1111/pirs.12360

Freeman RB (2016) Who Owns the Robots Rules the World. The deeper threat of robotization. Harvard Magazine. https://www.harvardmagazine.com/2016/05/who-owns-the-robots-rules-the-world. Accessed 20 December 2021

Frey CB, Osborne MA (2017) The future of employment: how susceptible are jobs to computerisation? Technological Forecasting and Social Change 114:254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Gordon R (2012) Is U.S. Economic Growth Over? Faltering Innovation Confronts the Six Headwinds. NBER Working Papers 18315. https://doi.org/10.3386/w18315

Görmar F, Lang T, Nagy E, Raagmaa G (2019) Re-thinking Regional and Local Policies in Times of Polarisation: An Introduction. In: Lang T, Görmar F (eds) Regional and Local Development in Times of Polarisation 1–2e. Palgrave Macmillan, Singapore

Gräbner C, Heimberger P, Kapeller J, Schütz B (2020) Structural change in times of increasing openness: assessing path dependency in European economic integration. Journal of Evolutionary Economics 30(5):1467–1495. https://doi.org/10.1007/s00191-019-00639-6

Graetz G, Michaels G (2017) Is modern technology responsible for jobless recoveries? American Economic Review 107(5):168–173. https://doi.org/10.1257/aer.p20171100

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

Green Leigh N, Kraft BR (2017) Emerging robotic regions in the United States: insights for regional economic evolution. Regional Studies 52(6):804–815. https://doi.org/10.1080/00343404.2016.1269158

Hall BH, Lotti F, Mairesse J (2013) Evidence on the impact of R&D and ICT investment on innovation and productivity in Italian firms. Economics of Innovation and New Technology 22(3):300–328. https://doi.org/10.1080/10438599.2012.708134

Hall PH, Heffernan SA (1985) More on the employment effects of innovation. Journal of Development Economics 17(1–2):151–162. https://doi.org/10.1016/0304-3878(85)90028-8

Hanson GH, Harrison AE (1995) Trade, technology, and wage inequality. NBER Working paper 5110. https://doi.org/10.3386/w5110

Herstad SJ, Sandven T (2019) A closer look at the relationship between innovation and employment growth at the firm level. Journal of Evolutionary Economics 30(2):375–399. https://doi.org/10.1007/s00191-019-00636-9

Herwartz H, Niebuhr A (2011) Growth, unemployment and labour market institutions: evidence from a cross-section of EU regions. Applied Economics 43(30):4663–4676. https://doi.org/10.1080/00036846.2010.493142

Iammarino S, Rodriguez-Pose A, Storper M (2019) Regional inequality in Europe: evidence, theory and policy implications. Journal of Economic Geography 19(2):273–298. https://doi.org/10.1093/jeg/lby021

International Federation of Robotics (2020) World Robotics Report 2020. International Federation of Robotics. http://reparti.free.fr/robotics2000.pdf. Accessed 11 Nov 2021

Jovanovic B, Rousseau PL (2005) General Purpose Technologies. In Aghion P, Durlauf S (eds) Handbook of Economic Growth 1(18). Elsevier, pp 1181–1224. https://doi.org/10.1016/S1574-0684(05)01018-X

Jovanovic B (2009) The technology cycle and inequality. The review of economic studies 76(2):707–729. https://doi.org/10.1111/j.1467-937X.2009.00532.x

Kemeny T, Petralia S, Storper M (2022) Disruptive innovation and spatial inequality. Regional Studies. https://doi.org/10.1080/00343404.2022.2076824

Kim L, Nelson RR (2000) Technology, Learning and Innovation: Experiences of Newly Industrializing Economies. Cambridge University Press, Cambridge

Krätke S (2007) Metropolisation of the European Economic Territory as a Consequence of Increasing Specialisation of Urban Agglomerations in the Knowledge Economy. European Planning Studies 15(1):1–27. https://doi.org/10.1080/09654310601016424

Lankisch C, Prettner K, Prskawetz A (2019) How can robots affect wage inequality? Economic Modelling 81:161–169. https://doi.org/10.1016/j.econmod.2018.12.015

Lee G (2009) International knowledge spillovers through the import of information technology commodities. Applied Economics 41(24):3161–3169. https://doi.org/10.1080/00036840701367515

Lee LF, Yu J (2010) Estimation of spatial autoregressive panel data models with fixed effects. Journal of Econometrics 154(2):165–185. https://doi.org/10.1016/j.jeconom.2009.08.001

Lund S, Cheng WL, Dua A, Smet AD, Robinson O, Sanghvi S (2020) What 800 executives envision for the postpandemic workforce. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/future-of-work/what-800-executives-envision-for-the-postpandemic-workforce. Accessed 11 December 2021

Manyika J, Chui M, Miremadi M, Bughin J, George K, Willmott P, Dewhurst M (2017) A future that works: Automation, employment, and productivity. McKinsey & Company. https://www.mckinsey.com/featured-insights/digital-disruption/harnessing-automation-for-a-future-that-works. Accessed 11 December 2021

McCann P, Ortega-Argilés R (2016) Smart specialisation, entrepreneurship and SMEs: issues and challenges for a results-oriented EU regional policy. Small Bus Econ 46:537–552. https://doi.org/10.1007/s11187-016-9707-z

McConnell MM, Perez-Quiros G (2000) Output Fluctuations in the United States: What Has Changed Since the Early 1980's? The American Economic Review 90(5):1464–1476. https://doi.org/10.1257/aer.90.5.1464

Mokyr J (2010) Chapter 2 - The Contribution of Economic History to the Study of Innovation and Technical Change: 1750–1914. In Hall B H, Rosenberg N (eds) Handbook of the Economics of Innovation 1. North-Holland, pp 11–50. https://doi.org/10.1016/S0169-7218(10)01002-6

Mondolo J (2021) The composite link between technological change and employment: A survey of the literature. Journal of Economic Surveys 1(42):1027–1068. https://doi.org/10.1111/joes.12469

Montobbio F, Staccioli J, Virgillito ME, Vivarelli M (2022) Robots and the origin of their labour-saving impact. Technological Forecasting and Social Change 174(121122). https://doi.org/10.1016/j.techfore.2021.121122

Moretti E (2012) *The New Geography of Jobs*. Houghton Mifflin Harcourt, New York

Moretti E (2013) Real Wage Inequality. American Economic Journal: Applied Economics 5(1):65–103. https://doi.org/10.1016/10.1257/app.5.1.65

Nuccio M, Guerzoni M, Cappelli R, Geuna A (2020) Industrial Pattern and Robot Adoption in European Regions. Università Ca' Foscari Venezia Working Paper 3. https://ssrn.com/abstract=3655140. Accessed 10 October 2022

OECD (1996) The knowledge-based economy. OECD Publishing, Paris

Pellegrino G, Piva M, Vivarelli M (2019) Beyond R&D: the role of embodied technological change in affecting employment. Journal of Evolutionary Economics 29(4):1151–1171. https://doi.org/10.1007/s00191-019-00635-w.5

Perez SA, Matsaganis M (2018) The Political Economy of Austerity in Southern Europe. New Political Economy 23(2):192–207. https://doi.org/10.1080/13563467.2017.1370445

Pigou A (1933) The Theory of Unemployment. Macmillan, London

Piketty T (2013) Capital in the 21st Century. Harvard University Press, Harvard

Piva M, Vivarelli M (2017a) Technological Change and Employment: Were Ricardo and Marx Right. IZA Discussion Paper 10471. https://doi.org/10.2139/ssrn.2903093

Piva M, Vivarelli M (2017b) Is R&D Good for Employment? Microeconometric Evidence from the EU. IZA Discussion Papers 10581. https://doi.org/10.2139/ssrn.2923667

Raspe O, Van Oort F (2006) The Knowledge Economy and Urban Economic Growth. European Planning Studies 14(9):1209–1234. https://doi.org/10.1080/09654310600933322

Say JB (1964) Treatise on political economy on the production, distribution and consumption of wealth. Claxton, Remsen & Haffelfinge, Philadelphia

Schumpeter J (1918) The Economics and Sociology of Capitalism. Princeton University Press, Princeton

Stiglitz JE (2013) The Price of Inequality: How Today's Divided Society Endangers or Future. W.W. Norton & Co, New York

Storper M (2018) Separate Worlds? Explaining the current wave of regional economic polarization. Journal of Economic Geography 18(2):247–270. https://doi.org/10.1093/jeg/lby011

Van Reenen J (1997) Employment and technological innovation: evidence from UK manufacturing firms. Journal of labor economics 15(2):255–284. https://doi.org/10.1086/209833

Van Reenen J (2011) Wage inequality, technology and trade: 21st century evidence. Labour economics 18(6):730–741. https://doi.org/10.1016/j.labeco.2011.05.006

van Winden W, van den Berg L, Pol P (2007) European Cities in the Knowledge Economy: Towards a Typology. Urban Studies 44(3):525–549. https://doi.org/10.1080/00420980601131886

Zhang P (2019) Automation, wage inequality and implications of a robot tax. International Review of Economics & Finance 59:500–509. https://doi.org/10.1016/j.iref.2018.10.013

Authors and Affiliations

Enzo Valentini[1] · Fabiano Compagnucci[2] · Mauro Gallegati[3] · Andrea Gentili[4]

Fabiano Compagnucci
fabiano.compagnucci@gssi.it

Mauro Gallegati
mauro.gallegati@univpm.it

Andrea Gentili
andrea.gentili@unint.eu

[1] Department of Political Science, Communication and International Relations, University of Macerata, Via Don Minzoni, 22, 62100 Macerata, Italy

[2] Social Sciences, Gran Sasso Science Institute (GSSI), Via Michele Iacobucci, 2, 67100 L'Aquila, Italy

[3] Department of Management, Università Politecnica delle Marche, Piazzale Martelli, 8, 60129 Ancona, Italy

[4] Faculty of Economics, Università degli Studi Internazionali di Roma, Via Cristoforo Colombo, 200, 00147 Roma, Italy