Dipartimento
Economia e Statistica
Cognetti de Martiis

Working Paper Series

26/20

LOCAL LABOR MARKET IMPACTS OF ADVANCED MANUFACTURING TECHNOLOGIES: EVIDENCE FROM EUROPEAN NUTS-3 REGIONS

GIANLUCA ORSATTI and FRANCESCO QUATRARO

Bureau of Research on Innovation, Complexity and Knowledge

Department of Economics and Statistics "Cognetti de Martiis"
Campus Luigi Einaudi, Lungo Dora Siena 100/A, 10153 Torino (Italy)
www.est.unito.it

UNIVERSITÀ DEGLI STUDI DI TORINO

The Department of Economics and Statistics "Cognetti de Martiis" publishes research papers authored by members and guests of the Department and of its research centers. ISSN: 2039-4004

Local labor market impacts of advanced manufacturing technologies: Evidence from European NUTS-3 regions

Gianluca Orsatti and Francesco Quatraro*

October 2020

Abstract

Based on the established literature about substitution and compensation effects, this paper provides one of the first analyses of the relationship between digital technologies and employment at the regional level in Europe. We posit that idiosyncratic factors of local labor markets are likely to generate place-specific responses to the introduction of new technologies. Spatial spillovers are also likely to emerge. The geographical level of analysis is therefore the most appropriate. Our analysis confirms that there is a significant relationship between the local specialization in advanced manufacturing technologies and employment. Mainly driven by automation-related technologies, we indeed estimate negative effects of advanced manufacturing technologies on local employment creation. Conversely, digital technologies play a positive role in enhancing local labor productivity. Finally, technological performances of neighbour regions play a significant role in shaping local labor productivity, while not significantly affecting local employment creation.

Keywords: Innovation, employment, digital technologies, local labour markets, spillovers
JEL Classification codes: O33, R11

*Gianluca Orsatti: Department of Economics and Statistics Cognetti de Martiis, University of Turin; E-mail: gianluca.orsatti@unito.it. Francesco Quatraro: Department of Economics and Statistics Cognetti de Martiis, University of Turin; E-mail: francesco.quatraro@unito.it

1 Introduction

Manufacturing firms worldwide are facing constant pressure to increase productivity by reducing the utilization of raw materials and energy. In this context, the German government launched in 2011 the platform *Industrie 4.0* to tackle the challenge and to improve the competitiveness of its firms. *Industrie 4.0* combines production methods with state-of-the-art information and communication technology (ICT). The driving force behind this development is the rapidly increasing digitalization of the economy and society. The technological foundation is provided by intelligent, digitally networked systems that will make largely self-managing and automated production processes possible. In the world of *Industrie 4.0*, people, machines, equipment, logistics systems and products will communicate and cooperate with each other directly. Production and logistics processes are integrated intelligently across company boundaries to make manufacturing processes more efficient and flexible. In September 2015, the European Parliament issued this paradigm defining *Industry 4.0* as the "fourth industrial revolution": it develops new ways of organizing production across the entire value chain.

While this "technological revolution" is expected to positively affect firms' productivity and international competitiveness, its impact on labor market dynamics is still an open, controversial question. Theoretically, automation, robots and artificial intelligence may indeed have a positive or a negative effect on employment and wages. The positive impact passes through the productivity effect, while the negative impact is due to displacement of worker skills (Acemoglu and Restrepo, 2017*b*). Scholars largely argue that accelerated automation of tasks performed by labor will make labor redundant (Brynjolfsson and McAfee, 2012; Akst, 2013). Indeed, as digital technologies, robotics and artificial intelligence penetrate the economy, workers will find it increasingly difficult to compete against machines, and their compensation will be likely to experience a relative or even absolute decline. Several recent papers try to both empirically and theoretically address this relationship (Sachs et al., 2015; Benzell et al., 2016; Acemoglu and Restrepo, 2017*a*,*b*). The extant evidence stresses that, through substitution, these technologies indeed wiped a large bunch of jobs.

However, these technologies also complement jobs. Complementarities, in turns, increase productivity, raise earnings and augment the demand for labor that, dynamically, modifies its skill composition. This last crucial set of mechanisms has been largely under-investigated by the extant literature (Dorn, 2015).

In this paper we investigate the relationship between employment dynamics and digital technologies in European NUTS-3 regions, over the period 1981-2007. Our analysis adds to the extant literature in several respects. First, it is worth noticing that most of the studies focus on a specific subset of the large bunch of technologies characterizing the so-called "fourth industrial revolution". Indeed, the main focus so far has been robotics and artificial intelligence. However, these technologies only partially characterize the *Industry 4.0* domain, which is much broader and dynamically evolving. We thus propose to investigate a more heterogeneous bunch of technologies, relying on the definition proposed by Aschhoff et al. (2010) of advanced manufacturing technologies (AMTs).

Furthermore, the extant literature almost always approached the study of the effect on labor dynamics by looking at the penetration and the diffusion of robotics and artificial intelligence in industries and local areas (i.e. Graetz and Michaels, 2015; Acemoglu and Restrepo, 2017*a*). This approach, we argue, is more likely to better capture substitution effects between automation and labor, while less saying about complementarity effects. To have a broader vision of the phenomenon at stake we instead propose to focus on where the creation of AMTs happens and at which intensity it evolves. For this reason, we collect precise information about the AMT-related patenting activity by looking at where inventors reside.

Our second original contribution to the literature is the geographical focus we propose. Indeed, while the largest part of the related studies targeted the U.S., we look at the European realm. Precisely, we investigate whether the local effort in developing AMTs affects both employment creation and labor productivity at the regional NUTS-3[1] level, collecting punctual data about local employment structures and AMT-related patents.

Our main findings are fourfold. First, we estimate negative effects of AMTs on employment. Second, when separately estimating the effect of specific AMTs on employment, we find that the negative effect is entirely driven by computer integrated manufacturing technologies and robotics. Third, we estimate positive effects of AMTs on local labor productivity. This positive effect is mainly driven by productivity growth within industries. Fourth, when separately estimating the effect of specific AMTs on labor productivity, we find very tiny or null effects of single, specific technologies. This last evidence highlights the importance of considering AMTs as a bunch of integrated technologies that develop new ways of organizing production across the entire value chain. To properly understand their effect on labor dynamics it is relevant to consider them as a whole.

The rest of the paper is structured as follows. Section 2 discusses the theoretical background. In Section 3 we describe both the data used and the methodologies applied. In Section 4 we report and discuss the results. Section 5 concludes.

2 Theory and hypotheses development

2.1 Innovation and employment: a non-straightforward relationship

The relationship between innovation activities and labor market dynamics has received much attention in economics, from both theoretical and empirical viewpoints.

The debate has focused on a number of distinct and yet related issues. On the one hand, a strand of the literature has focused on the impact of labor market dynamics on firms' innovation performance, paying particular attention to the effects of labor market deregulation and flexibility on firms' ability to successfully carry out more or less formalized innovation activities (Kleinknecht et al., 2014; Michie and Sheehan, 2003; Wachsen and Blind, 2016; Zhou et al., 2011).

On the other hand, the debate about the impact of innovation on employment has long attracted the attention of economics scholars, and is rooted in the seminal contributions by the founding fathers of the discipline. Theoretical and empirical studies put forth controversial evidence, being the relationship shaped by both potential compensation and replacement effects. (Pianta, 2005; Piva and Vivarelli, 2018).

This debate has been rejuvenated by the advent of the so-called ICT revolution, and more recently by the emergence of a new technological paradigm rooted in advanced digital technologies. Accordingly, following the well-known skill-biased technological change hypothesis, many studies have investigated the relationship

[1] Nomenclature of territorial units for statistics, see http://ec.europa.eu/eurostat/web/nuts/background

between technological change and the composition of the labor force in terms of skills distribution across firms and local areas (Acemoglu and Autor, 2011; Autor et al., 2003; Moretti and Thulin, 2013; Vona and Consoli, 2015).

The diatribe about the employment impact of innovation has been dominated by two different and yet complementary views. First, based on the former treatment by Ricardo (1951), there was much concern about the possible labor-saving nature of new machinery embodying new technologies. Ricardo's argument was however even much stronger, as it concerned not only labor demand, but also wages and national income (Samuelson, 1989).

Second, starting from the XIX century economists have identified a number of different mechanisms by which compensation effects can arise (Vivarelli, 2014). These forces are triggered by technological change and can counterbalance the labour saving impact of innovation.

Six main channels can be identified as drivers of the compensation effects. The first one concerns job production in the sector in which new machinery is produced. The second is related to the price decrease following technology-driven efficiency gains and overall cost reduction. In competitive markets cost effectiveness translates into lower prices for customers in final markets. Third, new investments are made possible via extra-profits accumulated in the short run, before system-wide market clearing and entry of suppliers. Fourth, in a neoclassical framework the substitution effect engenders a decrease in labour demand and the consequent decrease in wages that can eventually determine a shift back to more labour-intensive technologies. Fifth, in contexts characterized by strong trade unions' bargaining power, part of the gains stemming from increased efficiency can be redistribute to workers via income increase. Finally, technological change can also involve the introduction of new products and new branches, eventually leading to new job creation (Pianta, 2005; Vivarelli, 2014; Piva and Vivarelli, 2018; Vivarelli and Pianta, 2000; Freeman et al., 1982; Van Reenen, 1997).

2.2 Empirical evidence and the units of analysis

A wide body of empirical literature investigating the employment impact of innovation has been put forward. Much of this literature has focused on the impact of the so called ICT revolution that took place in the 1980s and 1990s.

These analyses have been carried out at different levels, from the micro to the macro one. As stressed by Vivarelli (2014), microeconometric analyses are well suited to investigate the differential impact of product and process innovation, the former being usually associated to new job creation while the latter to job destruction.

However, overall in microeconometric analyses there is the risk to overestimated the positive effects of innovation on employment, because of possible selection biases towards the most innovative, and hence better performing firms. Inter sectoral differences and crowding-out on competitors is generally neglected (Van Reenen, 1997; Piva and Vivarelli, 2018; Greenan and Guellec, 2000).

Sector-level studies allow to overcome this bias, providing evidence about intra-sectoral dynamics of innovation and employment. In these empirical settings both the positive performance of innovative firms and the indirect effects on the competitors can be taken into account.

The prevailing overall effect might however be ascribed to differences across sectors in terms of propensity to innovate, and more in general to the differential élasticityóf service vs. manufacturing sectors to the penetration of ICTs.

Accordingly, Antonucci and Pianta (2002) find evidence of a negative relationship between technological change and employment in manufacturing sectors. On the contrary, Evangelista and Savona (2002) provide evidence of a positive relationship for what concerns the service industries.

Both micro and sector-level studies are therefore characterized by possible biases in the analysis of the relationship between technological change and employment. Macro-level studies seem to be the best candidate to provide a comprehensive account of both direct and indirect effects.

By focusing on aggregate dynamics, these studies are able to encompass possible negative effects due to displacement, as well as the positive ones related to decreasing prices and increasing investments, job-creation and income increase. Macroeconomic studies have the advantage to address both intra-sectoral and inter-sectoral effects of innovation on employment.

There are a number of remarkable examples in this respect. Some of them are based on input-output relationships among sectors and provide evidence of positive and negative effects in different contexts, wherein the positive effects are not always able to offset the negative ones (Leontief, 1952; Whitley and Wilson, 1987; Meyer-Krahmer, 1992; Kalmbach and Kurz, 1990).

Other studies provided analyses within the context of partial or general equilibrium models, stressing that demand elasticity and factors' elasticity of substitution play a key role in the final assessment of the impact of innovation (Sinclair, 1981; Nickell et al., 1989).

Finally, a stream of macro-economic analyses has looked at general relationship between growth and employment within the context of macroeconomic models (Padalino and Vivarelli, 1997; Pini, 1996).

2.3 New digital technologies and employment in regional labor markets

The previous discussion highlighted that the relationship between innovation and employment is multifaceted, as at the system level it can involve different mechanisms. Accordingly, the choice of the level of analysis is important in order to provide a reliable account of the dynamics at stake.

While the extant literature provides important insights to better understand the impact of employment on innovation, the spatial dimension of local labour markets and innovation dynamics have been substantially neglected.

A few exceptions can be found in the literature. Capello and Lenzi (2013) investigate the effects of technological change on employment in European NUTS-2 regions. Using regionalized data from the Community Innovation Survey, they focus on the differential effects of product and process innovation on regional employment growth. Their analysis shows that place matters in that functional specialization and metropolitan settings influence the way regional labor markets appear to respond to technological change.

More recently, Cataldo and RodrÃguez-Pose (2017) have analyzed the source of cross-regional difference in employment growth, by looking at the effect of structural conditions, like the transport infrastructure, human capital and innovation. Their result about the impact of innovation, which is proxied by the count of patents in any technology at the local level, is not robust across the different specification.

These works emphasize that the regional level analysis of the impact of innovation on employment has many advantages. First, like macroeconomic analyses, it allows for the simultaneous account of both substitution and compensation effects. Second, place-specific conditions in terms of sectoral specialization and the presence of large cities may interfere with these dynamics. Third, labour markets are essentially local, as a large body of literature has stressed that the interaction between labour demand and supply is spatially bounded. Fourth, innovation dynamics are localized, as collective efforts of knowledge generation are the outcome of collaborative dynamics among innovating agents. Geographical proximity has been found to be a crucial determinant of the success of collective invention dynamics.

Moreover, Cataldo and RodrÃguez-Pose (2017) stress the importance of the characteristics of the regional economic structure, and of the patterns of reallocation of employment across sectors. Structural characteristics and structural change in turn show a clear regional variance (Quatraro, 2009).

Based on the previous considerations we are now able to spell out our working hypothesis as it follows.

Technological change can have both positive and negative effects on employment. Region-level analyses of these dynamics have the advantage of accounting for the different mechanisms underlying both types of effects. Moreover, these units of observation are more appropriate because of the place-specific and localized nature of labour market and innovation dynamics.

Digital technologies have been advocated in the last years as curse or bless, rejuvenating the debate about the job-creating or job-destructing effect of new technologies. In view of the geographical dimension of innovation and technological specialization, innovation in digital technologies in a specific area is expected to yield spill-overs over the employment dynamics of neighbor regions. The overall effect is expected to be positive (negative) if compensation effects dominate (are dominated by) the substitution ones.

3 Data, measures and empirical strategy

3.1 Data and measures

To study the relationship between the local creation and introduction of advanced manufacturing technologies (AMTs) and employment dynamics, we frame the analysis at the European NUTS-3 regional level. Employment and patent data are collected from 1981 to 2007 for 1,099 NUTS-3 regions, covering 25 EU countries.[2] Precisely, employment data come from the Cambridge Econometrics European Regional Dataset and patent data come from the OECD RegPat Dataset.

AMTs patent data According to Aschhoff et al. (2010), AMTs involve manufacturing operations that create high-tech products, use innovative techniques in manufacturing and invent new processes and technologies for future manufacturing. AMTs are capital intensive, knowledge intensive and demand high levels of intellectual capital. Their strength is built on strong human skills and a multi-disciplinary legacy in sciences including materials technology, ICT, mechatronics, physics, nanotechnology among others. AMTs are often characterized by a high level of numerical control and automation, customization, scalability and high skill-intensity. AMTs integrate information technologies and knowledge into manufacturing processes (e.g. digital production modeling, real time modeling of the factory, online non-destructive-testing) which help the optimization of production and factories.

[2]We do not consider the period after 2007 to avoid confounding effects due to the international economic crisis started in 2008.

Unlike other Key Enabling Technologies (KETs), AMTs comprise not a single technology but a combination of different technologies which include, among others, material engineering technologies (e.g. cutting, knitting, turning, forming, pressing, chipping), electronic and computing technologies, and their combination, measuring technologies (including optical and chemical technologies), transportation technologies and other logistic technologies.

To individuate AMTs we rely on the KETs taxonomy proposed by Aschhoff et al. (2010), based on the International Patent Classification (IPC). Patent information allow us to map the creation of AMTs at the local level. Precisely, we assign an AMT patent p to a NUTS-3 region r according to the information contained in the patent inventor's address. The OECD RegPat database indeed, for each patent-inventor pair, provides the corresponding NUTS-3 region of residence.

Once mapped AMTs at the local level, we build a measure of Revealed Technology Advantage in AMTs that region r at time t shows (RTA_{rt}). The measure follows the standard Balassa indicator for trade specialization, adapted to patent data. Formally,

$$RTA_{r,t} = \frac{\frac{AMTSTOCK_{r,t}}{TOTSTOCK_{r,t}}}{\frac{\sum_{r=1}^{m} AMTSTOCK_{r,t}}{\sum_{r=1}^{m} TOTSTOCK_{r,t}}} \tag{1}$$

where $AMTSTOCK_{r,t}$ is the stock of patents in AMTs assigned to region r at time t as described below, $TOTSTOCK_{r,t}$ is the total stock of patents assigned to region r at time t, and m is the total number of NUTS-3 regions in our sample.[3]

To account for possible spillover effects on employment dynamics of AMTs, we build an indicator of RTA in AMTs for neighboring NUTS3 regions ($SpillRTA$). For each region r at time t it takes value 1 if at least one neighboring region shows a revealed technology advantage in AMTs.

Employment data Local employment data come from the Cambridge Econometrics European Regional Dataset. We collect employment data at regional NUTS-3 level by economic activity (NACE Rev.2). To investigate the effect of the generation of AMTs on local employment dynamics we firstly look at the employment to population ratio shown by NUTS-3 region r at time t ($^{EMPL_{r,t}}/_{POP_{r,t}}$).[4]

Our interest turns then from labor creation to local labor productivity effects of AMTs. To do so, we perform a shift-share analysis. The shift-share analysis provides an interesting methodology that allows labor productivity to be decomposed in order to identify the differential contribution provided by changes in the reallocation of employment across sectors. We follow the approach developed by Fagerberg (2000), who decomposed labor productivity into three major components, i.e. the allocative and the productivity differential and interaction between the two.

[3] For robustness, we also implement a measure of AMT stock, calculated for each European NUTS 3 region r at time t ($AMTStock_{r,t}$) as:

$$AMTSTOCK_{r,t} = AMTPAT_{r,t} + (1-\delta)AMTSTOCK_{r,t-1} \tag{2}$$

where $AMTPAT_{r,t}$ is the number of patents in AMTs assigned to region r at time t and δ is the decay rate. We measure patent stocks applying the perpetual inventory method, allowing for a 15% annual rate of technological obsolescence (δ). To calculate the local AMT stock, we do not impose any arbitrary starting year for the series but we entirely exploit patent information provided by the RegPat dataset.

[4] Looking at employment to population ratio is the standard specification in the literature. Alternatively, we consider also log employment as our dependent variable ($logEMPL_{r,t}$).

A start is made by rearranging labor productivity as follows (region subscripts are omitted for the sake of clarity):

$$\frac{Y}{L} = \frac{\sum_j Y_j}{\sum_j L_j} = \sum_j \left[\frac{Y_j}{L_j} \frac{L_j}{\sum_j L_j} \right] \tag{3}$$

Labor productivity can therefore be decomposed into the contribution provided by labor productivity of each sector j as well as by the share of sector j in total employment. Let:

$$P_j = \frac{Y_j}{L_j} \tag{4}$$

$$S_i = \frac{L_j}{\sum_j L_j} \tag{5}$$

Then:

$$\frac{Y}{L} = \sum_j [P_j S_j] \tag{6}$$

The variation in labour productivity can therefore be expressed as follows:

$$\Delta \frac{Y}{L} = \sum_j [P_{j,t-1} \Delta S_j + \Delta P_j \Delta S_j + S_{j,t-1} \Delta P_j] \tag{7}$$

Equation (8) can be expressed in growth rates by dividing it by ${}^{Y}/_{L}$:

$$\frac{\Delta \left({}^{Y}/_{L} \right)}{\left({}^{Y}/_{L} \right)} = \sum_j \left[\frac{P_{j,t-1} \Delta S_j}{\left({}^{Y}/_{L} \right)} + \frac{\Delta P_j \Delta S_j}{\left({}^{Y}/_{L} \right)} + \frac{S_{j,t-1} \Delta P_j}{\left({}^{Y}/_{L} \right)} \right] \tag{8}$$

The first term in brackets on the right hand side of Equation (9) is the contribution to productivity growth from changes in the allocation of labor between industries. It will be positive if the share of high productivity industries in total employment increases at the expense of industries with low productivity. We define this term as μ in the empirical setting. The second term (π in the empirical analysis) measures the interaction between changes in productivity in individual industries and changes in the allocation of labor across industries. It will be positive if fast growing sectors in terms of productivity also increase their share in total employment. The third term (α in the empirical analysis) is the contribution from productivity growth within industries.

3.2 Empirical strategy

To investigate the relationship between AMTs and local employment creation we firstly estimate the following model:

$$ {}^{EMPL_{r,t}}/_{POP_{r,t}} = \beta_0 + \beta_1 RTA_{r,t-1} + \boldsymbol{X'_{r,t}} \beta_2 + \delta_t + \mu_r + \epsilon_{r,t} \tag{9}$$

where ${}^{EMPL_{r,t}}/_{POP_{r,t}}$ is the employment to population ratio of NUTS-3 region r at time t; $RTA_{r,t-1}$ is the revealed technology advantage in AMTs that region r at time $t-1$ shows; the vector $\boldsymbol{X'_{r,t}}$ contains (in most specifications) a set of controls for NUTS-3 region labor force, patenting activity and demographic composition that might independently affect innovation outcomes; δ_t and μ_r are time and regional dummies (NUTS-3 level) which capture, respectively, business cycle effects and territorial fixed effects; $\epsilon_{r,t}$ is the error term which captures possible unobserved shocks at the regional NUTS-3 level.

To account for possible AMT spillover effects on employment dynamics, we then augment equation (9) adding a dummy variable ($SpillRTA$) signaling for the presence of an RTA in AMTs in at least one neighboring NUTS3 region at time $t-1$. The augmented model is therefore:

$$^{EMPL_{r,t}}/_{POP_{r,t}} = \beta_0 + \beta_1 RTA_{r,t-1} + \beta_{12} SpillRTA_{r,t-1} + \boldsymbol{X'_{r,t}}\beta_3 + \delta_t + \mu_r + \epsilon_{r,t} \tag{10}$$

The second part of the analysis is instead dedicated to the investigation of the effect of AMTs on local labor productivity. To do so, we rely on the shift-share methodology, as described in Section 2.1. Precisely, we estimate the effect of RTAs in AMTs on, alternatively, the total local labor productivity ($LabProd$) and its components, i.e. changes in the allocation of labor between industries (*reallocation term* μ), the interaction between changes in productivity in individual industries and changes in the allocation of labor across industries (*cross-term* π), and the contribution from productivity growth within industries (*within-sector productivity* α). The four models are:

$$LabProd_{r,t} = \beta_0 + \beta_1 RTA_{r,t-1} + \beta_{12} SpillRTA_{r,t-1} + \boldsymbol{X'_{r,t}}\beta_3 + \delta_t + \mu_r + \epsilon_{r,t} \tag{11}$$

$$\mu_{r,t} = \beta_0 + \beta_1 RTA_{r,t-1} + \beta_{12} SpillRTA_{r,t-1} + \boldsymbol{X'_{r,t}}\beta_3 + \delta_t + \mu_r + \epsilon_{r,t} \tag{12}$$

$$\pi_{r,t} = \beta_0 + \beta_1 RTA_{r,t-1} + \beta_{12} SpillRTA_{r,t-1} + \boldsymbol{X'_{r,t}}\beta_3 + \delta_t + \mu_r + \epsilon_{r,t} \tag{13}$$

$$\alpha_{r,t} = \beta_0 + \beta_1 RTA_{r,t-1} + \beta_{12} SpillRTA_{r,t-1} + \boldsymbol{X'_{r,t}}\beta_3 + \delta_t + \mu_r + \epsilon_{r,t} \tag{14}$$

where explanatory variables and controls are as described in equations 9 and 10. Due to data availability about gross value added by economic sector at the NUTS3 level, the sample reduces copiously when measuring labor productivity.

For both cases (i.e. labor creation and productivity), we also estimate a series of regressions in which we break-down AMTs in their sub-components (i.e. computer, robotics, industrial measuring, industrial controlling, industrial regulating and machine tools).

3.3 Descriptive statistics

Table 1 provides basic descriptive statistics. Column 1 gives sample means and standard deviations for our variables. Panel A focuses on our dependent variables, while Panel B on some covariates. Columns 2-6 provide means and standard deviations by quartiles of the AMT stock measured at the local level.

It is interesting to observe that the employment to population ratio in 1981 was higher the higher the local stock of AMTs. Looking at average changes in employment to population ratio, NUTS-3 regions in the lowest quartile of the AMT stock show a decline, while regions in the rest of the distribution follow a similar (flat) positive trend. High standard deviations reveal that there is strong variability between the considered European areas.

With respect to labor productivity, differences between NUTS-3 regions at different quartiles of AMT patent stock are interesting. While experiencing declining trends in employment, areas in the lowest quartile of AMT stock experienced indeed the strongest growth in labor productivity, mainly driven by increases in the within-sector productivity. For the rest of the regions, labor productivity is lower the higher the stock of created AMTs.

This descriptive picture suggests that regions generating few AMTs are more labor productive (possibly through technological adoption). However, they are also more likely to experience drops in employment (possibly due to stronger displacement effects).

Panel B shows that there are no relevant differences in the industrial compositions between NUTS-3 regions at different quartiles of the AMT stock. Much pronounced differences instead emerge with respect to the average level of population. Indeed, areas with the highest AMT stock level are also, on average, more populated.

Table 1: Summary statistics

		QUARTILES OF AMT STOCK			
	ALL NUTS3	Q1	Q2	Q3	Q4
		Panel A: Employment			
	N=1,097	*N=211*	*N=411*	*N=304*	*N=171*
Employment to population ratio in 1981	0.45	0.39	0.42	0.47	0.49
	[0.13]	[0.12]	[0.12]	[0.13]	[0.16]
Change in employment to population ratio (in p.p.)	0.02	-0.2	0.06	0.07	0.007
	[4.74]	[5.73]	[4.29]	[4.69]	[4.39]
		Panel B: Labor productivity			
	N=277	*N=36*	*N=76*	*N=88*	*N=77*
Labor productivity	2.0	4.9	1.9	1.7	1.3
	[8.25]	[21.7]	[5.16]	[4.79]	[3.83]
Labor productivity: reallocation term	0.3	1.1	0.3	0.3	0.2
	[1.35]	[3.75]	[0.73]	[0.66]	[0.57]
Labor productivity: cross-term	-0.1	-0.6	-0.1	-0.06	-0.05
	[0.71]	[2.07]	[0.42]	[0.20]	[0.13]
Labor productivity: within-sector productivity	1.8	4.4	1.7	1.5	1.2
	[8.05]	[21.0]	[5.17]	[4.79]	[3.85]
		Panel C: Covariates			
	N=1,097	*N=211*	*N=411*	*N=304*	*N=171*
Share of employment in industry	0.2	0.2	0.2	0.2	0.2
	[0.097]	[0.094]	[0.094]	[0.094]	[0.10]
Share of employment in construction	0.08	0.08	0.08	0.08	0.07
	[0.030]	[0.039]	[0.031]	[0.025]	[0.020]
Population	352.1	318.9	282.2	336.8	569.7
	[363.1]	[225.1]	[272.0]	[336.0]	[561.3]

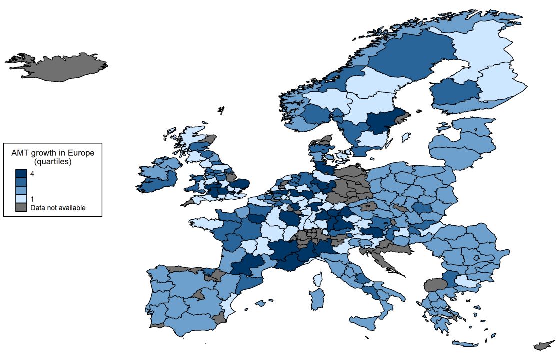
Notes: Sample means and standard deviations (in brackets) for the entire sample of NUTS-3 regions and by (population-weighted) quartiles of AMT patent stock distribution (1981-2011). Panel A includes employment variables, Panel B is for labor productivity and Panel C is for industry shares and population. Due to data availability on local value added, the sample importantly reduces when labor productivity is investigated. See text for variable definitions and sources.

We then report the geographic distribution of our main variables of interest. Figure 1 plots the quartile distribution of changes in AMT patenting activity in NUTS-2 regions during the period 1981-2011. Figure 2 instead provides a graphical representation of quartiles of average changes in employment to population ratio for the same period.

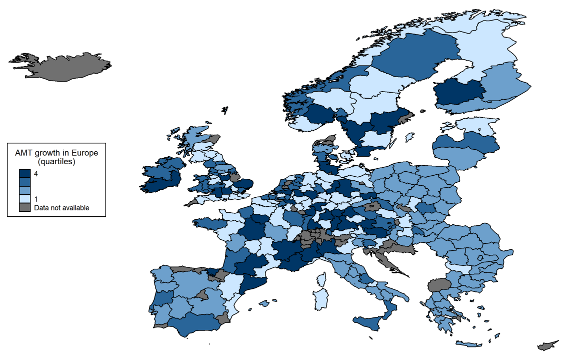
Looking at AMTs, it is interesting to observe that while more clustered in the early 1980s, their creation started involving a growing number of regions from 1990 on. However, regions in Germany, France, the UK, the north of Italy and in the Scandinavian area dominate the arena, while regions in more peripheral parts of Europe remain behind.

Turning to employment dynamics, figure 2 plots the geographic quartile distribution of changes in employment to population ratio. The four maps highlight that employment dynamics present high heterogeneity across countries and, more relevantly, within countries. This suggest that the choice of focusing on NUTS-3 areas is suitable to better capture this strong variability.

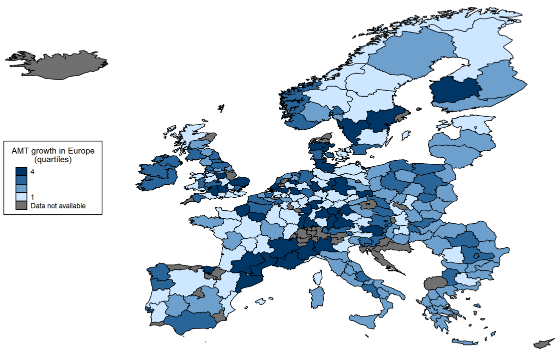
Figure 1: Growth in AMT patents (EU NUTS-2, 1981-2011)



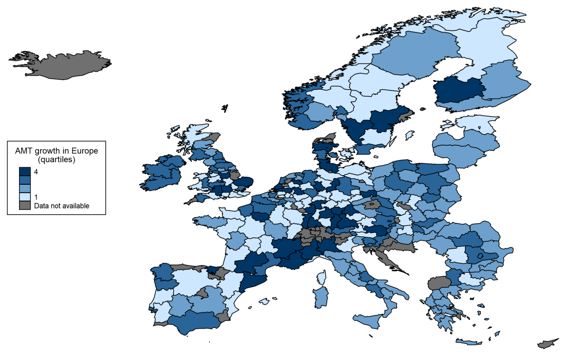
(a) 1981-1990



(b) 1991-2000



(c) 2001-2011



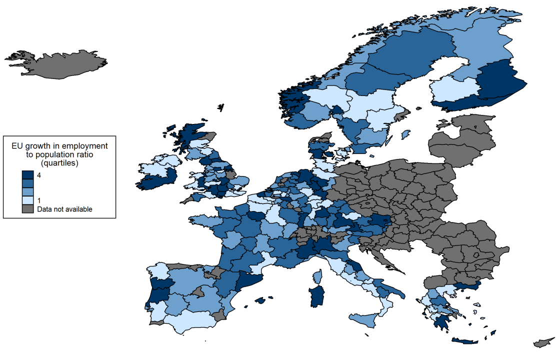
(d) 1981-2011

Note: The map depicts the the quartile distribution of changes in AMT patents at the NUTS-2 level from 1981 to 2011.

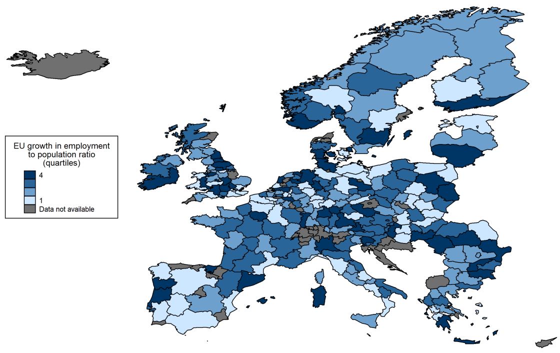
4 Results

In this section we present our main empirical results on employment and labor productivity at the European NUTS-3 level. We end our sample in 2007 to avoid potentially confounding effects of the international economic crisis started in 2008.

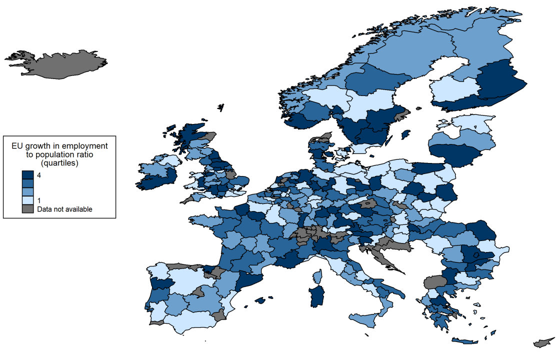
Figure 2: Changes in employment to population ratio (1981-2011)



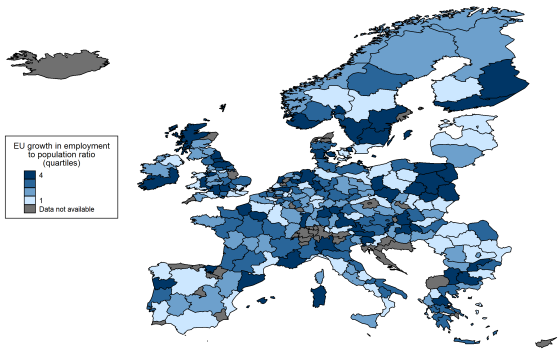
(a) 1981-1990



(b) 1991-2000



(c) 2001-2011



(d) 1981-2011

Note: The map depicts the quartile distribution of changes in employment to population ratio at the NUTS-2 level during the period 1981-2011.

4.1 Employment

Table 2 presents our main results for employment creation. The dependent variable is employment to population ratio defined as $100 \times {}^{EMPL_{r,t}}/_{POP_{r,t}}$. Our main specifications use, alternatively, the local revealed technology advantage in AMTs (columns 1-4) or the stock of AMTs (column 5) on the right-hand side. Moreover, we also include spatial technological spillovers to the analysis. All the specifications include NUTS-3 and year fixed effects. Unless stated otherwise, control variables included in the analysis are lagged one year. Standard errors are clustered at the NUTS-2 regional level to account for possible spatial correlation across local areas, and robust against heteroskedasticity.

Column 1 presents our most parsimonious specification, which only includes NUTS-3 and time fixed effects. We estimate a negative relationship between having a revealed technology advantage in AMTs and employment to population ratio in a NUTS-3 region with a coefficient of -0.27. This means that regions showing a revealed technology advantage in AMTs at time t experience on average a 0.27% drop in employment to population ratio at time $t + 1$.

In column 2 we control for employment and demographic local characteristics, including the level of employment, the share of employment in industry and the level of active population. This controls slightly attenuate the negative magnitude of our coefficient of interest that stands now at -0.23.

In column 3 we further control for the local general innovative effort, adding to the model the stock of patents in technologies not related to AMTs, invented by resident inventors. The coefficient for RTA_AMT is still significant and negative, with value -0.22.

In column 4, we add to the analysis a control for spillover effects. Precisely, we include the dummy variable $Spill\_RTA\_AMT$ that takes value 1 if at least one neighboring NUTS-3 region shows a revealed technology advantage in AMTs. We do not find a statistically significant coefficient for the spillover variable, concluding that being surrounded by areas specialized in AMTs is not detrimental for local employment. Controlling for potential geographic AMT spillovers does not affect our coefficient of interest, which is still significant and stable at -0.22.[5]

Finally, in column 5 we turn from RTA to the stock of AMTs in our estimation with the full set of controls, spillover variable included (that, for coherence, is now measured as stock). We estimate a significant and negative relationship between the stock of AMTs and employment to population ratio with a coefficient of -0.73. This confirms what found in previous estimates, when the local revealed technology advantage in AMTs was our variable of interest.

4.2 Labor productivity

We then turn to study the effect of the generation of AMTs on local labor productivity. Table 3 reports our results. All the specifications include NUTS-3 and time fixed effects, together with the full set of controls lagged one year, such as total employment, the industry share of employment, the level of active population, the stock of patents in non AMT fields and a control for AMT spillovers from neighboring regions. Standard

[5]To provide robustness checks of the impact of local RTA in AMT on employment creation, we estimate the model as the one proposed in column 4, Table 2, on two reduced samples: a) excluding NUTS-3 regions with null activity in AMT patenting; b) only NUTS-3 regions in the top 10 AMT patenting EU countries. Results based on these sub samples are fully consistent with the one reported in Table 2 and are reported in Table 5 in Appendix, Columns 1 and 3.

Table 2: The impact of AMTs on employment (1981-2007)

	Estimates for employment				
	(1)	(2)	(3)	(4)	(5)
RTA AMT	-0.27*	-0.23**	-0.22**	-0.22**	
	(0.14)	(0.10)	(0.097)	(0.095)	
Stock AMT					-0.73***
					(0.13)
Empl tot		30.9***	31.0***	31.0***	31.3***
		(1.90)	(1.92)	(1.92)	(1.96)
Empl share ind		-3.40	-3.03	-3.03	-4.20
		(2.69)	(2.74)	(2.73)	(2.69)
Active pop		-0.0095*	-0.0090*	-0.0090*	-0.0089*
		(0.0052)	(0.0053)	(0.0053)	(0.0053)
Stock non-AMT			-0.27	-0.27	0.018
			(0.17)	(0.17)	(0.14)
Spill RTA AMT				0.029	
				(0.10)	
Spill stock AMT					-0.13
					(0.17)
Time FE	Yes	Yes	Yes	Yes	Yes
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Observations	25,948	25,948	25,948	25,948	25,948
Adjusted R^2	0.910	0.961	0.961	0.961	0.962

The dependent variable is the employment to population ratio. All the models include NUTS-3 and time fixed effects. Explanatory variables lagged 1-year. Standard errors (in parentheses) are clustered at the NUTS-2 level and robust against heteroskedasticity. * $p < .1$, ** $p < .05$, *** $p < .01$

errors are clustered at the NUTS-2 level to account for possible spatial correlation across local areas and robust against heteroskedasticity.

Column 1 reports results for the total change in labor productivity. We estimate a positive effect of having an RTA in AMTs on the total productivity of labor at the local level. Precisely, the coefficient is 0.35.[6]

By relying on the shift-share methodology described in Section 2.1, we then estimate the effect of the local RTA in AMTs on *i)* changes in the allocation of labor between industries (column 2), *ii)* the interaction between changes in productivity in individual industries and changes in the allocation of labor across industries (column 3), and *iii)* the productivity growth within industries (column 4). Results reveal that the positive effect of the local stock of AMTs on labor productivity is driven by within-industry productivity changes. Indeed, the coefficient for $RTAAMT$ is significant and stands at 0.30 when the α measure is the dependent variable (Column 4). Interestingly, we estimate a significant and positive coefficient for AMT spillovers from neighboring areas ($spillRTAAMT$) on total labor productivity that, also in this case, seems to be driven by within-industry increases in productivity.

4.3 Employment and labor productivity per AMT sub-group

AMTs are composed by six main sub-groups: “robotics”, “computer integrated manufacturing”, “measuring of industrial processes”, “controlling industrial processes”, “regulating industrial processes”, and “machine tools”. We thus perform separate estimates for each of the six categories. Conditional on showing an RTA in AMTs, we investigate whether having a specific RTA in one of the six sub-groups of AMTs affects employment creation and labor produtivity.

Results are reported in Table 4. Column 1 reports results for employment creation, while columns 2-5 for labor productivity. In both cases we exactly reproduce the analysis described in sections 3.1 and 3.2, whose results are reported in Tables 2 and 3, but turning from focusing on the whole set of AMTs to the six sub-groups separately. All our specifications include the full set of controls, NUTS-3 and time fixed effects; standard errors are clustered at the NUTS-2 level to account for possible spatial correlation across local areas and robust against heteroskedasticity.

The emerging picture for employment dynamics is interesting and deserves further discussion. We indeed find two separate effects when splitting AMTs. On the one hand, we estimate negative coefficients only for computer manufacturing (which is significant) and robotics (not significant) on employment creation (column 1, Panels A and B). Coefficients are, respectively, -0.52 and -0.16. These technologies are more related to automation and artificial intelligence, therefore they are the best candidates for labor substitution. Our estimates on employment creation for these technologies are in line with previous studies (i.e. Acemoglu and Restrepo, 2017*a*). On the other hand, we estimate positive coefficients for technologies more directly related to industrial processes. Precisely, technologies related to measuring and regulating industrial processes have a positive and significant impact on employment to population ratio, with coefficients 0.22 and 0.21,

[6] To provide robustness checks of the impact of local RTA in AMT on labor productivity, we estimate the model as the one proposed in column 1, Table 3, on two reduced samples: a) excluding NUTS-3 regions with null activity in AMT patenting; b) considering only NUTS-3 regions in the top 10 AMT patenting EU countries. Results based on these sub samples are reported in Table 5 in Appendix, Columns 2 and 4.

Table 3: The impact of AMTs on labor productivity (1981-2007)

	Estimates for labor productivity			
	(1)	(2)	(3)	(4)
	total change	μ	π	α
RTA AMT	0.35**	0.041	0.0063	0.30**
	(0.14)	(0.029)	(0.013)	(0.15)
Empl tot	8.76**	1.04	0.75***	6.97**
	(3.79)	(0.94)	(0.23)	(2.88)
Empl share ind	-5.27	-1.94	-0.53	-2.80
	(5.61)	(1.90)	(0.77)	(4.08)
Active pop	0.0050	-0.0015	0.0042	0.0022
	(0.014)	(0.0041)	(0.0049)	(0.014)
Stock non-AMT	0.76*	-0.046	0.090	0.72*
	(0.45)	(0.070)	(0.071)	(0.41)
spill RTA AMT	0.59*	0.018	0.0050	0.57*
	(0.33)	(0.043)	(0.030)	(0.32)
Time FE	Yes	Yes	Yes	Yes
NUTS3 FE	Yes	Yes	Yes	Yes
Observations	6,975	6,975	6,975	6,975
Adjusted R^2	0.058	0.158	0.137	0.055

Dependent variables: total change in labor productivity (column 1); changes in the allocation of labor between industries (column 2); the interaction between changes in productivity in individual industries and changes in the allocation of labor across industries (column 3); and the productivity growth within industries (column 4). All the models include NUTS-3 and time fixed effects. Explanatory variables are 1-year lagged. Standard errors (in parentheses) are clustered at the NUTS-2 level and robust against heteroskedasticity. The number of observations reduces with respect to estimates on employment creation due to missing data for value added. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: The impact of AMTs on employment and labor productivity, specific technologies (1981-2007)

	Estimates for employment and labor productivity				
	Employment	Labor productivity			
	(1)	(2)	(3)	(4)	(5)
	Empl pop ratio	Total change	μ	π	α
	Panel A: Computer integrated manufacturing				
RTA computer	-0.52***	-0.26**	-0.028	0.017	-0.25**
	(0.16)	(0.12)	(0.039)	(0.015)	(0.12)
	Panel B: Robotics,				
RTA robotics	-0.16	0.27	0.029	0.001	0.24
	(0.11)	(0.20)	(0.032)	(0.015)	0.20)
	Panel C: Measuring of industrial processes,				
RTA measuring	0.22***	0.098	-0.001	0.001	0.098
	(0.075)	(0.16)	(0.032)	(0.012)	(0.17)
	Panel D: Controlling industrial processes				
RTA controlling	0.007	-0.006	0.013	-0.003	-0.016
	(0.11)	(0.19)	(0.018)	(0.011)	(0.18)
	Panel E: Regulating industrial processes				
RTA regulating	0.21**	-0.022	0.020	0.018*	-0.060
	(0.087)	(0.16)	(0.034)	(0.010)	(0.15)
	Panel F: Machine tools				
RTA machine	0.12	0.059	0.018	-0.005	0.046
	(0.091)	(0.14)	(0.026)	(0.012)	(0.13)
Observations	25,948	6,975	6,975	6,975	6,975

Each Panel refers to estimates for employment creation and productivity effects of specific AMTs. All the models include NUTS-3 and time fixed effects, and the full set of controls lagged one year: total employment, industry share of employment, active population, stock of non-AMT patents and AMT geographical spillovers. Standard errors are clustered at the NUTS-2 level and robust against heteroskedasticity. Column 1 reports estimates for employment to population ratio. Column 2-5 report estimates for labor productivity measures: total change in labor productivity (column 2), changes in the allocation of labor between industries (column 3), the interaction between changes in productivity in individual industries and changes in the allocation of labor across industries (column 4), and the productivity growth within industries (column 5). The number of observations reduces when estimating the effect on labor productivity due to missing data for value added. * $p < .1$, ** $p < .05$, *** $p < .01$

respectively (Column 1, Panels C and E). It is worth to notice here that these results suggest the existence of complementarity between technologies more strictly related to industrial processes and local employment, with the latter increasing as a response to their generation and diffusion.

Turning then to the effect on labor productivity, we estimate significant coefficients only for computer integrated manufacturing technologies and regulating industrial processes technologies. The former have a negative effect on total changes in labor productivity (-0.26), driven by within-industry effects (-0.25). The latter have a positive impact (0.018) on the interaction between changes in productivity in individual industries and changes in the allocation of labor across industries: a local area with an RTA in this kind of technologies is more likely to increase employment of fast growing sectors in terms of productivity.

In all, the effect on labor productivity of single AMTs seems to be negligible. However, as reported in Table 3, the entire bunch of AMTs is responsible for positively contributing to local labor productivity. Taken together, these results therefore suggest that focusing on single technologies may provide a partial understanding of the phenomenon. Taking them as a whole, and possibly considering their mix, is instead mo e appropriate for r comprehensive appreciation of their impact on labor dynamics.

5 Conclusions

This paper investigates the effect of the generation of advanced manufacturing technologies on employment and labor productivity in Europe between 1981 and 2007. Precisely, we frame the analysis at the regional NUTS-3 level, collecting data about local employment structures and AMT-related patents.

We estimate negative effects of AMTs on employment creation. However, when separately estimating the effect of specific AMTs, we find that this negative effect seems to be entirely driven by computer integrated manufacturing technologies and robotics. Interestingly, we indeed find positive effect on employment of technologies related to measuring and regulating industrial processes. It is worth noticing that computer integrated manufacturing technologies and robotics are strictly attached to automation, thus more suitable for substituting labor. Technologies that refer to industrial processes have instead broader application and, presumably, may complement human tasks. Through complementarities, these technologies may thus increase employment, partially attenuating negative substitution effects due to pure automation.

Looking at labor productivity, we estimate a positive effect of AMTs. This effect is mainly driven by productivity growth within industries. We do not find any effect on changes in the allocation of labor between industries. Interestingly, when separately estimating the effect of specific subgroups of AMTs on labor productivity, we find very tiny or null effects of single technologies, with the exception of computer integrated manufacturing technologies that seem to negatively impact total labor productivity (again, passing through reduction in within-industry productivity). This evidence suggests that focusing only on specific subsets of AMTs (i.e robotics and artificial intelligence) may give a partial interpretation of the phenomenon, with the risk of over- or under-estimating the real effect that the emergence of new production processes may have on labor dynamics.

As for spatial spillover effects, we find that the innovative performance in AMTs of neighboring regions has a positive impact on local labor productivity, while showing a non significant relationship with local employment creation.

References

Acemoglu, D. and Autor, D. H. (2011), Skills, Tasks and Technologies: Implications for Employment and Earnings, *in* D. Card and O. Ashenfelter, eds, 'Handbook of Labor Economics', Vol. 4B, Elsevier, Amsterdam, NL, pp. 1043–1171.

Acemoglu, D. and Restrepo, P. (2017*a*), Robots and Jobs: Evidence from US Labor Markets, NBER Working Papers 23285, National Bureau of Economic Research, Inc.

Acemoglu, D. and Restrepo, P. (2017*b*), The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment, NBER Working Papers 22252, National Bureau of Economic Research, Inc.

Akst, D. (2013), *What Can We Learn From Past Anxiety Over Automation?*, Wilson Quarterly.

Antonucci, T. and Pianta, M. (2002), 'Employment effects of product and process innovation in europe', *International Review of Applied Economics* **16**(3), 295–307.

Aschhoff, B., Crass, D., Cremers, K., Grimpe, C. and Rammer, C. (2010), European Competitiveness in Key Enabling Technologies, Technical report, Centre for European Economic Research (ZEW).

Autor, D. H., Levy, F. and Murnane, R. J. (2003), 'The Skill Content of Recent Technological Change: An Empirical Exploration', *The Quarterly Journal of Economics* **118**(4), 1279–1333.

Benzell, S. G., Kotlikoff, L. J., LaGarda, G. and Sachs, J. D. (2016), Robots Are Us: Some Economics of Human Replacement, NBER Working Papers 20941, National Bureau of Economic Research, Inc.

Brynjolfsson, E. and McAfee, A. (2012), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, W. W. Norton Company.

Capello, R. and Lenzi, C. (2013), 'Innovation and employment dynamics in european regions', *International Regional Science Review* **36**(3), 322–353.

Cataldo, M. D. and RodrÃguez-Pose, A. (2017), 'What drives employment growth and social inclusion in the regions of the european union?', *Regional Studies* **51**(12), 1840–1859.

Dorn, D. H. (2015), 'Why Are There Still So Many Jobs? The History and Future of Workplace Automation', *Journal of Economic Perspective* **29**(3), 3–30.

Evangelista, R. and Savona, M. (2002), 'The impact of innovation on employment in services: evidence from italy', *International Review of Applied Economics* **16**(3), 309–318.

Freeman, C., Clark, J. and Soete, L. (1982), 'Unemployment and technical innovation: A study of law', *London: Frances Printer* .

Graetz, G. and Michaels, G. (2015), Robots at Work, CEP Discussion Paper 1335, Centre for Economic Performance.

Greenan, N. and Guellec, D. (2000), 'Technological innovation and employment reallocation', *Labour* **14**(4), 547–590.

Kalmbach, P. and Kurz, H. D. (1990), 'Micro-electronics and employment: a dynamic input-output study of the west german economy', *Structural Change and Economic Dynamics* **1**(2), 371–386.

Kleinknecht, A., van Schaik, F. N. and Zhou, H. (2014), 'Is Flexible Labour Good for Innovation? Evidence from Firm-Level Data', *Cambridge Journal of Economics* **38**(5), 1207–1219.

Leontief, W. (1952), *Machines and Man*, Scientific American.

Meyer-Krahmer, F. (1992), 'The effects of new technologies on employment', *Economics of Innovation and New Technology* **2**(2), 131–149.

Michie, J. and Sheehan, M. (2003), 'Labour Market Deregulation, 'Flexibility' and Innovation', *Cambridge Journal of Economics* **27**(1), 123–143.

Moretti, E. and Thulin, P. (2013), 'Local Multipliers and Human Capital in the United States and Sweden', *Industrial and Corporate Change* **22**(1), 339–362.

Nickell, S., Komg, P. et al. (1989), Technical progress and jobs, Technical report.

Padalino, S. and Vivarelli, M. (1997), 'The employment intensity of economic growth in the g-7 countries', *Int'l Lab. Rev.* **136**, 191.

Pianta, M. (2005), Innovation and Employment, *in* J. Fagerberg, D. Mowery and R. R. Nelson, eds, 'Handbook of Innovation', Oxford University Press, Oxford, UK, pp. 568–598.

Pini, P. (1996), 'An integrated model of cumulative growth: Empirical evidence for nine oecd countries, 1960-1990', *LABOUR* **10**(1), 93–150.

Piva, M. and Vivarelli, M. (2018), 'Technological Change and Employment: Is Europe Ready for the Challenge?', *Eurasian Business Review* **8**(1), 13–32.

Quatraro, F. (2009), 'Innovation, structural change and productivity growth: evidence from Italian regions, 1980â2003', *Cambridge Journal of Economics* **33**(5), 1001–1022.

Ricardo, D. (1951), 'On the principles of political economy and taxation, 1st'.

Sachs, J. D., Benzell, S. G. and LaGarda, G. (2015), Robots: Curse or Blessing? A Basic Framework, NBER Working Papers 21091, National Bureau of Economic Research, Inc.

Samuelson, P. A. (1989), 'Ricardo was right!', *The Scandinavian Journal of Economics* pp. 47–62.

Sinclair, P. J. (1981), 'When will technical progress destroy jobs?', *Oxford Economic Papers* **33**(1), 1–18.

Van Reenen, J. (1997), 'Employment and technological innovation: evidence from uk manufacturing firms', *Journal of labor economics* **15**(2), 255–284.

Vivarelli, M. (2014), 'Innovation, employment and skills in advanced and developing countries: A survey of economic literature', *Journal of Economic Issues* **48**(1), 123–154.

Vivarelli, M. and Pianta, M. (2000), *The employment impact of innovation: evidence and policy*, Routledge London.

Vona, F. and Consoli, D. (2015), 'Innovation and Skill Dynamics: A Life-Cycle Approach', *Industrial and Corporate Change* **24**(6), 1393–1415.

Wachsen, E. and Blind, K. (2016), 'More Labour Market Flexibility for more Innovation? Evidence from Employer-Employee Linked Micro Data', *Research Policy* **45**(5), 941–950.

Whitley, J. D. and Wilson, R. (1987), 'Quantifying the impact of information technology on employment using a macroeconomic model of the united kingdom economy', *Information Technology and Economic Prospects* pp. 1901–1906.

Zhou, H., Dekker, R. and Kleinknecht, A. (2011), 'Flexible Labor and Innovation Performance: Evidence from Longitudinal Firm-Level Data', *Industrial and Corporate Change* **20**(3), 941–968.

Appendix – Robustness checks

Table 5: The impact of AMTs on employment an labor productivity (1981-2007)

	Only patenting NUTS-3		Top 10 EU countries	
	(Empl)	(Prod)	(Empl)	(Prod)
	(1)	(2)	(3)	(4)
RTA AMT	-0.21**	0.12	-0.22**	0.12
	(0.098)	(0.11)	(0.098)	(0.11)
Empl tot	31.8***	1.85	31.6***	1.98
	(2.58)	(1.27)	(2.51)	(1.29)
Empl share ind	-3.70	1.19	-2.86	1.10
	(3.18)	(2.02)	(3.13)	(2.09)
Active pop	-0.024***	0.0067	-0.024***	0.0079
	(0.0084)	(0.0081)	(0.0085)	(0.0086)
Stock NO AMT	-0.65***	-0.38*	-0.67***	-0.39*
	(0.19)	(0.20)	(0.19)	(0.21)
Spillr RTA AMT	-0.13	0.22	-0.097	0.22
	(0.11)	(0.16)	(0.11)	(0.15)
Time FE	Yes	Yes	Yes	Yes
NUTS3 FE	Yes	Yes	Yes	Yes
Observations	19,849	6,034	20,366	6,120
Adjusted R^2	0.971	0.123	0.970	0.128

Columns 1 and 2 report estimates for, respectively, employment creation and labor productivity when the sample is reduced to NUTS-3 regions with at least one patent in AMTs. Columns 3 and 4 report estimates for, respectively, employment creation and labor productivity when the sample is reduced to NUTS-3 regions in the top 10 AMT-patenting EU countries. All the models include NUTS-3 and time fixed effects. Explanatory variables lagged 1-year. Standard errors (in parentheses) are clustered at the NUTS-2 level and robust against heteroskedasticity. * $p < .1$, ** $p < .05$, *** $p < .01$