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Skill up:
Smart work, occupational mix and regional productivity

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ABSTRACT

New technologies and sector imbalances due to manufacturing hollowing out have dented the regional stock of competencies in the EU labour markets. This raises concerns over the sustainability of the EU's competitiveness in the longer term. The present study sheds light on what occupational mix might be able to deliver greater regional productivity in the light of emerging industrial dynamics. We estimate panel regression models using regional data from the EU Labour Force Survey and Eurostat regional statistics. Our results show that regional gross value added is significantly improved if regions have a mix of occupations that includes what we define as smart workers: these are workers employed in advanced manufacturing and knowledge-based production-support activities. We also test interactions amongst production and production-support occupations as well as the non-linear effect between smart workers and regional gross value added. Policy implications are discussed.

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1. INTRODUCTION

In the last decades, European economies have experienced substantial changes in their labour force composition. There has been a process of a job polarisation (Goos and Manning, 2007), characterised by a rise of employment in both the highest-skilled (professional and managerial) and lowest-skilled (personal services) occupations, along with declining employment for mid-skill jobs (manufacturing and routine office jobs) (Goos et al., 2009). Technological progress (Autor et al., 2003) and globalisation (Blinder, 2009b) are mainly blamed for this trend. Over the recent decades, technological change has altered the job skill demands in advanced economies (Chennells and Reenen, 1999; Acemoglu, 2002; Autor et al., 2003) with mechanisation and automation complementing labour input for non-routine cognitive tasks (Spitz-Oener, 2006), whilst displacing routine manual and routine cognitive tasks. Some of these have migrated to take on routine tasks in service occupations, such as cleaning and desk clerking.

In parallel, processes of industrial transformation (Frenken et al., 2015) have delineated how European manufacturing has been the subject of an intense reorganisation driven crucially by multinational firms' offshoring strategies. EU multinational companies have mainly devoted their efforts to presiding over high value-added upstream and downstream activities, whilst offshoring low value-added operations to lower labour cost economies. Manufacturing offshoring has led to an erosion of Marshallian externalities and manufacturing skills in EU manufacturing regions so crucial for the growth and wealth creation of high-income economies in the past (Christopherson and Clark, 2007; Bailey et al., 2010). More recently, Pisano and Shih (2012) and Berger (2013) argue that deindustrialisation is fundamentally also threatening EU innovation capabilities (Buciuni et al., 2014). Such a threat is particularly critical if we consider the pivotal role that manufacturing still plays in European economies: each additional manufacturing job is found to be able to create 0.5-2 jobs in other sectors in Europe (Rueda-Cantuche et al., 2012). In 2012, manufacturing represented the second largest sector within the EU-28's non-financial economy in terms of its contribution to employment (22.4%) and value added (26.2 %) (EUROSTAT, 2015).

New technologies and the hollowing out of manufacturing activities have impacted on the EU labour market: they have affected EU job demand, as well as the local and regional stock of competences, raising concerns over the sustainability of EU competitiveness longer term. Scholars have acknowledged that such changes are impacting on the job composition with fears of an increasing skill mismatch in advanced economies (amongst others, Crinò, 2009; Feenstra, 2010; Kemeny and Rigby, 2012). Yet understanding what job profiles are needed to sustain economic growth across the EU is overlooked (see for exception, Manca, 2012).

Our main research question is, therefore, aimed at addressing this gap by measuring what occupational mix is found to be able to deliver greater regional productivity. In particular, this work aims at extrapolating what occupational mix might be needed in advanced economies in the light of the emerging industrial dynamics associated with a new manufacturing model - Industry 4.0 or 'smart' manufacturing - where production and knowledge-based production-support capabilities are increasingly symbiotic and mutually constructive (Lowe and Wolf-Powers, 2018). The adoption of automation and digital technologies across the manufacturing spectrum is shaping a new production model, where digitally enabled technologies are applied in manufacturing processes and products (ZongWei, 2014; Kiel et al., 2017; Wiegmann et al., 2017: 1371). Building on a rising literature that explores how new 'smart' technologies (Wiegmann et al., 2017: 1370) and 'smart' products embodying such technologies (Porter and Heppelmann, 2014) are shaping and supporting major ongoing industrial trends, we define *smart workers* as those workers undertaking production and knowledge-based production-support occupations (Lowe and Wolf-Powers, 2018) in digital and manufacturing sectors (Wiegmann et al., 2017). These workers are an expression of complementary digitally-based competences and experience-based competences (Amison and Bailey, 2014). We test their contribution to regional productivity as against other occupations.

The paper empirically addresses this issue by using regional data from the European Union Labour Force Survey (EU-LFS) and Eurostat regional statistics. The combination of these sources enables us to create a balanced panel for European local labour market NUTS-II areas from 2011 to 2014. This study focuses on eight European countries which have similar advanced manufacturing industries. Panel regression models are performed to study which occupational mix might lead to higher productivity, measured as Gross Value Added (GVA) per employee. We test empirically whether a mix of occupations, including smart workers, positively contributes to regional GVA.

The paper is organised as follows: the current debate on industrial changes and job composition is discussed in Section 2. Section 3 introduces the novel concept of smart work. Section 4 describes dataset and models. Section 5 discusses the empirical results and robustness checks. Finally, Section 6 presents concluding remarks by illustrating contributions to the regional studies and economic geography literature as well as policy recommendations.

2. INDUSTRIAL CHANGES AND JOB RE-COMPOSITION

2.1 The impact of offshoring on job composition

The fast pace of globalisation often associated with the rise of multinational enterprises (MNEs) has not only scaled up trade globally, but, more crucially, it saw the cross-border fragmentation of production with the emergence of an international division of labour that stretches from advanced economies such as Europe, North America and Japan, for the first time to South East Asia, South Asia and Latin America. Such cost-saving strategies led to the offshoring of the most labour-intensive production functions to low cost economies (Bailey and De Propris, 2014) and the loss of 'production and operative occupations' in the home economies (Acemoglu and Autor, 2011). The emergence of global value chains (GVC) (Gereffi et al., 2001) in the 1990s and early 2000s was an indispensable move for manufacturing firms located in advanced countries, seeking to maintain some competitive advantage in markets dominated by price competition. Initially, companies in high-income economies benefited from the relocation of production by stimulating specialisation by function within each industry, instead of sector (Robert-Nicoud, 2008) and, consequently, by retaining higher value added activities in their domestic base.

However, manufacturing offshoring changed the composition of local labour markets. The slow depletion in the stock of skills that are "*genomic, catalytic, organic and dynamic,* (whilst) *capable of nourishing, sustaining*" (Kasabov and Sundaram, 2016: 1529) local industrial heritage over time generated skill atrophy in the laid-off workers (Bailey and de Ruyter, 2015). This has, overall, jeopardised EU socioeconomic resilience. Recent contributions have looked at the impact of offshoring on the composition of the skills pool (e.g. Morrison, Paul and Siegel, 2001; Falk and Koebel, 2002; Hijzen et al., 2005) and the tasks actually performed (Markusen, 2005; Robert-Nicoud, 2008; Jensen and Kletzer, 2010).

Various classifications of tasks are currently accepted, including: tradable and non-tradable tasks (Blinder, 2009a; Jensen and Kletzer, 2010); abstract, routine and service tasks (Goos et al., 2008; 2009); or, again, routine and non-routine jobs (e.g. Autor et al., 2003). They share an understanding that tasks capture a distinct dimension of workforce composition, only partly related to the conventional distinction between white-collar or bluecollar or to the classification that draws on educational attainment (Becker et al., 2013: 103). Indeed, some argue that task trade with developing economies is responsible for current structural transformations occurring in labour markets in advanced economies (Jones and Kierzkowski, 1990; Baldwin and Robert-Nicoud, 2007; Kohler, 2009; Levy and Murnane, 2012). In particular, physical and cognitive tasks that can be routinised and codified were more likely to be subject to offshoring (Baldwin and Robert-Nicoud, 2007; Grossman and Rossi-Hansberg, 2008; Robert-Nicoud, 2008; Kohler, 2009). Accordingly, 'safer' jobs tended to be more 'immobile' -i.e. attached to more place-bound occupations- and those requiring higher levels of interpersonal interaction and/or complex problem solving.

Exploring the relationship between offshoring and domestic workforce composition, evidence shows a re-composition from routine to non-routine tasks, with growing interpersonal and analytical tasks (for the German case, see Becker et al. 2013; for the US case, see Kemeny and Rigby, 2012; and, for the UK case, see Gagliardi et al., 2015). Analysing the effect of the offshoring activities undertaken by British-based MNEs, Gagliardi et al. (2015) find that offshoring led to the destruction of jobs in routine occupations, especially in sectors more exposed to MNE relocation, due to their initial industry specialisation in more routine activities. Overall, such results support Iammarino and McCann (2013), who find that international fragmentation of the production and technology diffusion catalysed international convergence, whilst triggering subnational polarisation and divergence. In summary, in advanced economies, global production and the expansion of the service sector have driven a demand for high skill, relatively non-routine tasks, specifically with high levels of interpersonal interaction.

2.2 The impact of technological change on job composition

The skill-biased technological change literature has shown that, recently, in advanced economies the introduction of new technologies has altered the skill demand in the manufacturing sector (e.g. Chennells and Reenen, 1999; Katz and Autor, 1999; Acemoglu, 2002; Autor et al., 2003, Kemeny and Rigby, 2012). Industrial structural changes induced by the diffusion of digital technology have led to labour mobility, as an adjusting mechanism to the economic shocks (Martynovich and Lundquist, 2015). New technologies tend to replace labour functions causing job losses in declining sectors, some of which migrate to other expanding sectors (Mortensen and Pissarides, 1998).

Looking at how tasks demanded in jobs have altered due to an increase in firms' computer capital investment in the US between 1960 and 1998, Autor et al. (2003) find that (within industries, occupations and education groups) computerisation mostly displaced labour input of codified and programmable tasks (such as, routine manual and routine cognitive ones). At the same time, computerisation complemented labour input of non-routine cognitive tasks (such as those demanding flexibility, creativity, generalised problem-solving capabilities and complex communications). Equally, investment in computer capital has boosted educated labour over the past three decades. Other advanced economies - such as Germany - experienced similar changes in their labour market, with more complex skill requirements (especially for computerising occupations) leading to about 36% of the recent educational upgrading in employment (Spitz-Oener, 2006: 236). In line with these findings, analysing computer adoption in US manufacturing, Kemeny and Rigby (2012) show that the presence of interactive and analytical tasks was positive and significantly related to capital intensity; whereas, they do not find a significant link between non-routine task and technological changes (albeit positive). Like the impact of offshoring on job composition, Autor and Dorn (2013: 1553) find that the adoption of information technology in local labour markets specialised in routine tasks led to low-skill tasks being reallocated to service occupations (employment polarisation) and, at the same time, earnings growth was pooled at the two tail-ends of the distribution (wage polarisation).

Currently, the diffusion of an unfolding new wave of 'smart' technologies (Wiegmann et al., 2017) [1] is driving a disruptive re-composition of skills and competences. OECD (2016: 4) warns that "rapid technological change could challenge the adequacy of [today] skills and training systems" leading to skills obsolescence. The displacement of workers performing routine manual and routine cognitive tasks (OECD, 2017, Rifkin, 2013) would nevertheless leave people with creative and entrepreneurial competences with "comparative advantage over machines" (Annunziata and Biller, 2014: 13).

2.3 The impact of job composition on regional performance

Europe is experiencing a skills mismatch with skill demand struggling to meet supply due to over- and under-supply of skills by level and subject, as well as skill obsolescence (Skills Panorama, 2016). Besides, according to the *Cedefop's European Skills and Jobs* (ESJ) *Survey*, on average, 45% of EU adult employees across eight macro groups of occupation (elementary occupation, plant and machine operators, skilled agricultural workers, service and sales, clerical support, technicians and associate professionals, professional, and managers) believe that several of their skills will become outdated in the next five years (Cedefop, 2015). Skill mismatch has a considerable impact on the economic performance and economic growth of regions and countries. The skill composition of regional labour markets is argued to provide economic resilience, improve regional performance and deliver regional growth. Evidence suggests that a strong base of skilled workers represents a more reliable

[1] 'Smart' technologies are usually defined as digitally enabled technology and automation (e.g. sensors, wireless web based-cloud communication technology and networks, intelligent robots and machines, and Big Data).

and critical source of long-run urban health (Glaeser, 2005; Treado, 2010). Indeed, in a path-dependent perspective, the pools of skills present in a region can act as the repository of knowledge and resources, sustaining value-creation (Kasabov and Sundaram, 2016) as well as making regional economies resilient longer term (Christopherson et al., 2010; Simmie and Martin, 2010; Bailey and de Ruyter, 2015).

Skill transfer and skill sharing are amongst the most important prerequisites to activate synergies amongst firms located in the same region (Porter, 1985). Indeed, the "critical ingredient of reinvention [or, in some cases, of perseverance] is human capital" (Glaeser, 2005: 152). Boschma and Capone (2016: 619) reported examples of the role played by skills in sustaining regional economic development. Regions endowed with a sectoral portfolio that consists of industries requiring similar kind of skills relatedness (e.g. Neffke et al., 2018) reabsorb unemployed better than regions with a portfolio of unrelated industries (Diodato and Weterings, 2015). High-quality regional matching of skills promotes production complementarities stimulating regional productivity growth (Boschma et al., 2014). Regions can better respond to sector-specific shocks when endowed with more portable skills across jobs (Nedelkoska and Neffke, 2010; Nedelkoska et al., 2015), such as skills linked to new general purpose technologies[2] - i.e. information and communication technologies (ICT), electronic, and digitalisation.

The local socioeconomic fabric can be strengthened by coupling the set of pre-existing skills with new competences and capabilities coming from emerging new technologies. As described in the ethnographic study by Kasabov and Sundaram (2016: 1530) on Coventry (UK), the "inherited skills like artisanal talent, craftsmanship, design and innovation […] augmented by engineering, manufacturing, fabrication and prototyping

[2] 'General Purpose Technologies' (GPT) are technologies characterised "by the potential for pervasive use in a wide range of sectors and by their technological dynamism. As a GPT evolves and advances it spreads throughout the economy, bringing about and fostering generalised productivity gains. Most GPT's play the role of 'enabling technologies', opening up new opportunities rather than offering complete, final solutions" (Bresnahan and Trajtenberg, 1995: 84).

acquired in the industrial era" have nourished economic growth of the areas. This result calls for further research investigating the effects of the combinations of these skills on the regional economy (Bellandi et al., 2017). Complementarities between traditional and advanced manufacturing as well as between manufacturing and services are crucial in re-rooting regional economies to new growth paths (Amison and Bailey, 2014). In particular, the manufacturing sector can act primarily as a stabilising factor (i.e. helping regions to retain workers), whilst services drive labour reallocation by attracting workers to regions (Martynovich and Lundquist, 2015). The embedded sector composition of a region shapes its ability to react and adapt to changes. From an evolutionary approach to regional resilience, places endowed with industrial diversity appear to be less sensitive to economic shocks (e.g. Boschma and Iammarino, 2009; Christopherson et al., 2010; Clark et al., 2010; Neffke et al., 2011; Boschma, 2015). Conversely, regions with a specialised industrial structure (Boschma and Lambooy, 1999) have more limited re-combinatory options (Frenken et al., 2007; Hidalgo et al., 2007) available at the regional scale to recover from sector-specific shocks and/or generate new growth paths.

The current debate points to the pervasive impact of digital technologies in production and consumption, inducing a 'structural change' that - according to the definition by Neffke et al. (2018) – "implies a transformation, not just of the local industry mix but also of the local capability base sustaining this mix" (Neffke et al., 2018: 25). New business models in manufacturing force a shift from a product-based business model to a service-based business model (Lafuente et al., 2016). At the same time, new market dynamics are re-shaping the competitive environment in which firms operate and value is created through the value chain, drawing on the co-innovation with customers/users. Personalisation, made-to-order and customer co-innovation address a demand for unique and bespoke products and experiences by consumers who want to be actively involved in the production process (Boër et al., 2004;

Deloitte, 2015). Due to changes in technologies and final demand, some capabilities inevitably become obsolete, pushing regions to renew/upgrade their capability bases in order to avoid decline (Neffke et al., 2018).

This literature does not consider, however, which skill composition is required for a sustained economic growth. Building on work by Di Liberto (2008) and Manca (2012) on human capital, we explore what skills mix might be able to deliver greater regional productivity. Looking at the impact of human capital composition on regional catch-up in Spain over the period 1960–1997, Manca (2012: 1384) showed "how tertiary education positively drives economy convergence at both high and low development stages. [...] Empirical evidence indicates that along with tertiary education, secondary and vocational training also plays an important role in the productivity catch-up of richer regions (while it does not play a substantial role for poorer region)." In the next section, the paper presents a first step towards unpacking a sort of 'skill chain' that includes skill sets associated with new trends in manufacturing and services.

3. SMART WORKERS

Disruptive changes in the cross-border fragmentation of production, technologies and final demand seem to require a new regional base of skills and capabilities. Given their portability, competences in engineering (e.g. Boschma et al., 2014), applied sciences, maths, stats (e.g. Wright et al., 2017), creative tasks (Florida, 2014) as well as design of goods and services (Christopherson, 2009; Clark, 2014; Lowe and Wolf-Powers, 2018) play a critical role in regional economies. For instance, amongst others, the presence and their inter-firm mobility of engineering capabilities are highly valued in several manufacturing and services industries (Song et al., 2003; Neffke et al., 2018).

In particular, the emerging advanced manufacturing model needs a mixture of skilled professionals, technicians and manual skilled workers in order to employ the sophisticated instruments and equipment required to manufacture products (Lyons, 1995). Pfeiffer and Suphan (2015) argue that competences in digitally-enabled technologies must, however, be complemented with 'experience-based knowledge' in many areas of production, assembly and maintenance. The co-presence of these different competences allows to tackle and resolve situations characterised by complexity and unpredictability, such as those imbued with a combination of new artisanal talent, craftsmanship and authenticity. High-tech manufacturing needs specialised machine operators, as well as craft workers, working side by side with designers and engineers. Berger (2014) argues that 'interdisciplinary' skills enabling collaboration and cross-cultural interactions will be crucial. Indeed, current and future manufacturing challenges combine the original craft production model with the complexities of using advanced systems and technologies (Boër et al., 2004). Designers and artisans themselves have already 'upgraded' their skills by adopting new technologies such as CAD and 3D printers. Design-oriented occupations also have changed their role in the value chain, and exercise their creativity, not in isolation, but among a team of other professionals, including engineers (Sennett, 2008; Bettiol and Micelli, 2014: 15).

This dovetailing of new technologies-based and experience-based knowledge characterises, for instance, the *makers*' movement (Hatch, 2013). Makers are boundary spanners across craft production combining design and fabrication of products, and often experimental digital technologies (Wolf-Powers et al., 2017). Makers have encouraged a wave of new small-scale manufacturing enterprises that integrate design with production; they can be business-to-consumer and business-to-business (Anderson, 2012). Preliminary studies of makers' contribution to local economic development in Chicago (IL), New York City (NY), and Portland shows that, although they *emerge as place-based manufacturers* who make products in a place and who contribute most directly to a locality's employment growth ((Wolf-Powers et al., 2017: 365-367), they are *global innovators* offering products, processes and materials innovations straight to global markets.

Equally disruptive is expected to be the re-composition of skills inside 'smart' factories where automation and digital technology is expected to replace "*workers doing routine, methodical tasks,* [however] *machines can amplify the comparative advantage of those workers with problem-solving, leadership* […] *and creativity skills"* (PwC, 2016: 30). Indeed, "*technological progress, notably in high-performance computing, robotics and artificial intelligence, is extending the range of tasks that machines can perform better than humans can,* [but] *the shift will push a growing share of the workforce towards creativity and entrepreneurship, where humans have a clear comparative advantage over machines"* (Annunziata and Biller, 2014, 13). Again, it is also argued that the adoption of digitally-enabled technologies will increase the need for people able to "*apply much more specialised knowledge and experience-based knowledge [...] in many areas of production, assembly and maintenance"* (Pfeiffer and Suphan, 2015).

Drawing upon the literature on technological change in the new economic geography, we present a new category of workers, which we label *smart workers.*[3] These are workers undertaking production and knowledge-based production-support occupations (Lowe and Wolf-Powers, 2018) belonging to the ICT, manufacturing and service fields (Wiegmann et al., 2017). These workers are an expression of complementary digitally-based competences (such as: competences on analytics, data architecture, machine learning, coding and human-

[3] Jobs have been classified according to several definitions. Autor et al. (2003), Acemoglu and Autor (2011) and Gagliardi et al. (2015) classify jobs according to two dimensions: non-routine/routine and cognitive/manual. Dustmann et al. (2005) defined jobs according to skilled, unskilled and semi-skilled. The category 'skilled workers' includes the professions with the highest hourly wages: employers and managers, professional workers, and employees with the armed forces. The category 'semiskilled workers' includes intermediate non-manual workers, junior non-manual workers, and foremen and supervisors. Finally, the category 'unskilled workers' includes farmers and farm workers, manual workers and personal service workers (Dustmann et al., 2005). Alternatively, Wixe (2015) as well as Johansson and Klaesson (2011) group workers according to the presence of cognitive skills, management and administration skills, social skills, or motoric and other skills. We decided to develop a new classification since previous classifications fail to capture the mix of skills we deem relevant in the context of recent disruptive changes in the cross-border fragmentation of production, technologies and final demand.

machine interaction) and experience-based skills (such as: artisanal talents in craft productions; see: Amison and Bailey, 2014; Kasabov and Sundaram, 2016) critical in the emerging industrial mix.

More specifically, *smart* workers perform manual and cognitive tasks that require technical knowledge, analytics capabilities, problem-solving, intuition, creativity, precision and manual dexterity:[4] tasks explicitly mentioned or implied by - amongst others - Boschma et al. (2008; 2014), Anderson (2012), Florida (2014), Autor (2015) and Lowe and Wolf-Powers (2018). These workers have skills that can be deployed in the factory or independently. They are a subset of four macro groups of production (first two groups) and knowledge-based production-support (second two groups) occupations: i) plant and machine operators, and assemblers; ii) craft workers and related trade workers; iii) technicians and associate professionals; and iv) professionals. For instance, within the 'plant and machine operators, and assemblers' group, we define smart workers as shoemaking and related machine operators, and mechanical machinery assemblers. Within 'craft workers and related trade' group, we consider smart workers as aircraft engine mechanics and repairers, and handicraft workers. Within 'technicians and associate professionals' group, we select information and communication technicians, and process control technicians. Finally, within the 'professional' group, we define smart professional workers as mathematicians, and statisticians, as well as industrial and production engineers (see Appendix A for more details).

We decide to use an occupation-level analysis[5] in the light of the work on skill relatedness, according to which the industry-specificity of skills do not have to be absolute,

[4] World Economic Forum (2016: 22, Table 10).

[5] Traditionally, research on skills is inclined to equate skill to education attainment (Bacolod et al., 2009; 2010). The choice of using education attainment as a proxy for skills is also dictated by a superior data quality in many datasets. However, growing research on skill mismatch (OECD, 2011; Hamersma et al., 2015) highlights how education differs from skills. "Education is a characteristic of a person and is related to the qualifications and knowledge acquired through formal education. Skills, on the other hand, are a requirement of a job and are related to competences and expertise acquired through experience and the training a person needs to possess to fill that job" (Broersma et al., 2016: 1678). Also, occupation

as it is more likely that some specialised skills can be valuable also in a range of related industries (Neffke and Henning, 2013). Accordingly, we test the contribution of composition and complementarities amongst jobs to regional level economic performance, comparatively with other standard factors such as R&D investment and industrial diversity.

4. DATA AND MODEL

To determine what occupational mix might be able to deliver greater regional productivity, the paper uses both microdata from the European Union Labour Force Survey (EU-LFS)[6] and regional statistics collected by EUROSTAT. We examine eight European countries with similar manufacturing industries (Austria, Belgium, France, Germany, Greece, Italy, Spain and Sweden).[7] Variables and data sources are summarised in Table 1. Merging these sources enables us to create a balanced panel for European local labour market NUTS-II areas from 2011 to 2014.[8] To understand the contribution of smart workers and their interaction with other types of workers to regional productivity, we measure regional

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provides a more meaningful (Florida et al., 2011) and a "potentially more robust measure of utilized skill—that is how human talent or capability is absorbed by and used by the economy […] occupation is the mechanism through which education is converted into skill and labour productivity" (Florida et al., 2008: 618). Formal education provides an incomplete picture of human capital (Lucas, 1977). Learning-by-doing dynamics can allow low-educated workers to acquire competences that enable them to apply for jobs requiring higher skill levels than those acquired through formal education. Conversely, during the economic crisis, highly educated workers had to accept jobs demanding lower skills. An increasing number of studies in urban and regional have turned to occupational measures as more direct measure of skills (Feser, 2003; Markusen and Schrock, 2006; Florida et al., 2008; Florida, 2014), showing that occupational measures outperform educational attainment in accounting for regional development (Marlet and Van Woerkens, 2004; Mellander and Florida, 2006).

[6] The EU-LFS is the largest European household sample survey, providing quarterly and annual data on labour participation of people aged 15 and over and on persons outside the labour force. It covers residents in private households (excluding conscripts) according to labour status. Each quarter, some 1.8 million interviews are conducted throughout the participating countries to obtain statistical information for some 100 variables. The sampling rates in the various countries vary between 0.2 % and 3.3 %.

[7] We chose these eight countries, as, according to the 2011-2014 EU-LFS guidelines, they have used sampling plans which involved stratifications at the regional level. We did not take into consideration weights as the weighting procedure used by these eight countries involves differ calibration estimators. According to Eurostat guidelines, data regarding Austria, Belgium, France, Greece and Italy are subject to a limited reliability *(limit 'b')* due to the total of the weighted population.

[8] Studies at the country level use Travel to Work Areas (TTWAs), defined as self-contained labour markets, as the main referenced for measuring labour market (Casado-Díaz, 2000) However, from the Council Regulation EEC No. 577, the Council of the European Union established minimum requirements in terms of sample error of the EU-LFS in order to guarantee trustworthy at least regional representation defined at NUTS-II level.

competitiveness in terms of regional productivity, hence GVA per employee (Wosnitza and Walker, 2008; Artis et al., 2011: 1174).[9]

Table 1 about here

The estimations are performed using the pooled Ordinary Least Squares (OLS), the fixed effects (FE) and generalised method of moments (GMM) methods. To address the likely correlation between the error term over time for a given region, cluster-robust standard errors are used to check the statistical significance of the parameters (e.g. Lisciandra and Millemaci, 2017). In the pooled OLS estimations, the regional specific effects are ignored, whilst the FE panel models allow us to control for unobserved heterogeneity. The empirical FE model is the following:

$$GVA\ per\ employee_{t,r} = c + \beta_1 OccupationalMix_{t,r} + \beta_2 Z_{t,r} + \mu_r + \omega_{t,r} \quad (1)$$

where:

r = region (NUTS-II area);
t = year;
$OccupationalMix_{t,r}$ = shares of workers performing a given job over the total number of workers in the region r at time t;
$Z_{t,r}$ = control variables (R&D investment and diversity workers in the region r at time t) (Wixe, 2015);
μ_r = regional fixed effects controlling for time-invariant unobservable regional characteristics;
$\omega_{t,r}$ captures the remaining disturbances.

Unobserved time-invariant region-specific effects are removed from a panel model by using FE estimator. Time fixed effects are added as dummy variables to address common

[9] The rationale of using GVA per employee as a regional performance indicator (e.g. Manca, 2012) instead of GDP per capita (amongst others, Vandenbussche et al., 2006) is that the latest is a standard measure to compare levels of economic activity across regions with different population size (Abel and Gabe, 2011) which underpins a deeper attention to the welfare of the sampled regions.

period-specific shocks (Kemeny and Rigby, 2012). Country fixed effects are considered as dummy variables to control for country-specific shocks and different national institutional contexts. Finally, we control for potential endogeneity as a result of reverse causality by employing an instrumental system-GMM estimator (López-Bazo and Motellón, 2012).

4.1. Explanatory variables

We are interested in exploring the contribution of production and knowledge-based production-support occupations, expression of digitally-based and experience-based skills, to regional performance in the context of three main disruptive changes: i) the cross-border fragmentation of production, ii) the adoption of new 'smart' technologies, and, iii) final demand. Accordingly, the vector of occupations (occupational mix) represents our key explanatory variable. This variable is calculated using information from the International Standard Classification of Occupations (ISCO-08). We look at different types of occupations and their combinations: managers; professionals; technicians and associate professionals; clerical support workers; service and sales workers; craft and related trades workers; and plant, machine operators and assemblers. Table 1 reports how these occupations are measured in detail. In particular, we compute smart workers as the share of workers (over the total number of workers in the region) in both manufacturing and services sectors. Smart workers consist of a subset of four macro groups of production (craft workers and plant workers, respectively category 7 and category 8 in ISCO-08) and knowledge-based production-support occupations (professionals and technicians, respectively category 2 and category 3 in ISCO-08) related to complex production processes in advanced manufacturing and knowledge-based services (see Appendix A for more details).

Furthermore, we break down the smart workers classification at a fine-grained level to single out occupations that are linked to artisanal talents, which are rooted in the industrial competences of regions (amongst others, garment workers, wood workers, handicraft jewellery workers, toolmakers, and/or aircraft engine mechanics). These jobs are an expression of experience-based, 'know-how process-development skills' (Pisano and Shih, 2012: 2) endangered by deindustrialisation and whose disappearance is threatening EU innovation capabilities in a wide range of industries. Such jobs are underpinned by experience-based skills that cannot be automated, but are complementary to automation. They are associated with handling complexity and unpredictability, linked to delivering customisation and co-innovation with customer or supplier (Christopherson and Clark, 2007; Pisano and Shih, 2012; Berger, 2013). We define the category of 'smart craft workers' as artisanal talents rooted in the industrial competences of regions; such as: metal, machinery and related trades workers (category 72 in ISCO-08); handicraft and printing workers (category 73); wood treaters, cabinet-makers and related trades workers (category 752); and garment and related trades workers (category 753) (further details in Table 1 and Appendix A). More specifically, we compute smart craft workers as a dummy variable, whose value is equal to one if 1 if the share of smart craft workers over the total workforce in the region *r* at time *t* is equal or above the 25th percentile. Using this category, we evaluate the effect on regional productivity of the co-presence of these traditional artisanal talents with workers equipped with talents in production-support activities (such as technicians and professionals).

4.2. Control variables

Following the literature on regional resilience, the sectoral portfolio of a region can affect its competitiveness. To control for Jacobs externalities or *industrial diversity*, we measure industrial entropy (Jacquemin and Berry; 1979, Attaran, 1986) as the distribution of the employees across industries at NUTS-II level according to the following formula:

$$D_r = -\sum_{i=1}^{n} \left(\frac{e_{i,r}}{e_r}\right) \ln \left(\frac{e_{i,r}}{e_r}\right) \quad (2)$$

where D_r measures diversity in NUTS-II r; $e_{i,r}$ is the number of employees in one-digit industry i and NUTS-II r; and e_r is the total number of employees in municipality r (Wixe, 2015). In order to capture how much a region is investing in new technology, we include the total intramural R&D expenditure by all sectors and NUTS-II regions (*R&D investments*); it is taken with three-year lag. Table 2 provides some descriptive statistics of the dataset. Table 3 reports pairwise correlations among all the variables.

Tables 2 and 3 about here

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5. RESULTS AND DISCUSSION

The results of the estimations are presented in Tables 4 and 5. Models 1-7[10] explore the impact of the presence of smart workers along with managers, service and sales workers as well as clerical support workers on regional GVA. Model 1 and 2 provide the results for the pooled OLS estimations, whilst Model 3 and 4 provide the results for the FE[11] ones. In the baseline pooled OLS estimations (Model 1), where the regional specific effects are ignored, the estimated effect for the presence of smart workers, managers and clerical workers is positive and highly statistically significant. The estimated effect of the presence of service and sales workers is negative, but not statistically significant. Except for smart workers, the results slightly change when unobserved time-invariant region-specific effects are removed

[10] In multivariate tests based on the pooled OLS model (Model 2 with d), the mean variance inflation factor (VIF) is 2.89 with a maximum of 5.07. Even in the model with fixed regional effects, the mean VIF is 2.89 with a maximum of 4.81. All VIFs are well below the rule-of-thumb threshold of ten (Kennedy, 2003: 213), this suggests little collinearity.

[11] We also carried out the Hausman test to compare between fixed effects model and random effects model in panel data. Results suggest that the FE model is preferred (chi2(6) = 84.89, *p-value* = 0.00).

from a panel model by using FE estimator (Model 3). Indeed, the estimated effect of the presence of smart workers, which represents the predictor of main interest in this paper, is still positive and statistically significant (ß = 0.22). A 1% increase in the proportion of smart workers is associated with about a 22% increase in regional GVA. Thus, results seem to suggest that production and knowledge-based production-support occupations, expression of complementary digitally-based and experience-based skills critical in the emerging industrial mix represent a particularly important driver of regional GVA. However, conversely to smart workers, the estimated effects for managers and clerical workers remain positive, but are not statistically significant. The effect for the presence of service and sales workers is positive and statistically significant in the model with control variables.

In model specification 2 (pooled OLS) and 4 (FE), regional characteristics are introduced (such as R&D investments and industrial diversity). Following previous studies (amongst others, Lucas, 1988; Romer, 1990; Bronzini and Piselli, 2009), R&D investment has a positive and statistically significant impact on regional GVA. The coefficient of industrial diversity is positive, but not statistically significant. The absence of a statistically significant (although positive) result could lie on the coarse level, according to which the regional sectoral portfolio variety has been measured, due to data availability. We suspect that a more fine-grained measure, such as the one used by Frenken et al. (2007), would lead to stronger impact of industrial diversity on regional GVA in line with the literature on regional resilience (Christopherson et al., 2010; Simmie and Martin, 2010; Bailey and de Ruyter, 2015). The robust pooled OLS standard errors are substantially higher than the robust FE standard errors. We perform F-test of the joint significance of the fixed effects intercepts to compare pooled OLS estimations with FE ones. The null is rejected (F test (140, 416) = 284.86, *p-value* = 0.00), leading us to conclude that FE models are preferred to pooled OLS models.

To address the possibility that the presence of smart workers may be the result of higher regional economic performance instead of the cause of it, we use an instrumental variable (IV) estimation.[12] To construct the IV, we focused on the variables that are related to the presence of new technologies and their applications in advanced manufacturing production processes associated with occupations carried out by smart workers. We used high-tech patent applications to the EPO by priority year by NUTS-II regions from EUROSTAT[13] in years 1998, 1999, 2000 and 2001. We ultimately settle on lagged total high tech, computer and automated business equipment, and communication technology patent applications as an instrument for smart workers. To ascertain if each IV is a good predictor (Luthi and Schmidheiny, 2013) of smart workers, we run a Stock and Yogo (2002) weak instrument test. It compares the first-stage *F*-statistic with a critical value which varies according to the number of endogenous variables, the size of the instruments and the tolerance for the 'size distortion' of a test (α = 0.05) of the null hypothesis that the instruments are weak (Gabe and Abel, 2015). The null hypothesis of weak instruments can be rejected by a test using a 10% maximal size threshold. We can cautiously conclude that the instruments are not weak using 10% maximal size threshold for Models 5-7. The three instruments pass the Kleibergen-Paap under-identification test, which means that they cannot be considered weak. Our primary interest is in testing the contribution of smart workers on regional GVA. Models 5-7 show that the effect for the presence of smart workers is positive and statistically significant. These results obtained using IVs to control for the reverse causality broadly conform to the uninstrumented results concerning smart workers, proving further support to the positive (and statistically significant) impact of smart workers on regional productivity.

[12] In order to develop an IV approach, identifying variables that are correlated with occupational mix (relevant), but not directly related to the regional economic performance (exogenous), is required.
[13] Variables labelled [dataset pat_ep_rtec] in the EUROSTAT regional statistics.

Table 4 about here

Models 8 and 9 test the presence of a non-linear effect between smart workers and GVA. In Model 8, smart workers do not show a non-linear effect with GVA. The absence of a non-linear effect implies that there is not an inverted U-Shaped relationship linking smart workers and regional GVA. In other words, the positive effect of smart workers on GVA does not drop as the share of smart workers in the industrial structure increases. Conversely, it gets stronger as the presence of smart workers rises. The findings are confirmed in Model 9, where regional control variables are added to the estimation. In line with Model 3, the positive link between managers, service and sales workers, and clerical support workers on GVA is not statistically significant (Model 8). As in Model 4, where regional characteristics are introduced in the estimation, Model 9 shows that service and sales workers are positive and statistically significant at the 10% significance level. As in Models 2 and 4, R&D investments have a positive and statistically significant impact on regional GVA.

We test the role of *smart craft workers* in Models 10-13 (Table 5). Model 10 represents the baseline model to test the effect of the co-presence of technicians and smart craft workers. Models 11 estimates the interaction term between technicians and smart craft workers on regional GVA. More interestingly, we find that the co-presence of technicians and smart craft workers in a region positively and statistically significantly impacts on the regional GVA in Model 11 ($ß = 3.02$). Models 12 and 13 test the interaction term between professionals and smart craft workers on regional GVA. Likewise, we find that the combination of professionals and smart craft workers boosts regional productivity, as they show a complementary added effect. This result seems to highlight two aspects. Firstly, the importance of sustaining jobs (such as craftsmanship talents) that are an expression of experience-based knowledge, ‘know-how process-development skills’ and crucial for regional innovation capabilities in a wide range of industries (Christopherson and Clark, 2007; Pisano and Shih, 2012). Secondly, although deindustrialisation thinned some of these competences out, they are now understood to be crucial for the regional economy if combined with talents in production-support activities (such as technicians and professionals). Professionals show a negative effect on GVA; such an impact is statistically insignificant in Model 12, but statistically significant in Model 13 (at the 10% significance level). However, managers, service and sales workers, clerical support workers, technicians and plant, machine operators, and assemblers have a positive (albeit, not always statistically significant) impact on GVA in Models 12-13.

Table 5 about here

In summary, smart workers show positive and statistically significant estimated effects on regional GVA across all the models. The presence of managers, clerical support workers, service and sales workers (with the exception of Models 1 and 2) and technicians is positively related (even though not always statistically significant) to regional productivity. Our findings show negative, but either statistically not significant (Models 10-12) or slightly statistically significant (at the 10% significance level in Model 13), estimated effects for professionals. One possible explanation could lie in the fact that the category ‘professionals, is quite heterogeneous. Amongst professionals, ISCO-08 classification includes health professionals, business and administration professionals as well as legal professionals. Due to their nature, the impact of these jobs on regional GVA appears to be limited.

The present findings show that regions endowed with a portfolio of skills, including smart craft workers and technicians as well as professionals, emerge to have higher GVA. We find complementarities between smart craft workers and technicians as well as professionals. New technologies (such as 3-D printing, robotics, cloud computing, etc.) are revolutionising the industrial mix of advanced countries. In particular, the implementation of digital technologies in manufacturing sectors allows factories to combine new technologies with know-how heritage embedded in craft workers. This draws attention to the re-emergence of a demand for craft-based top end products along with new flexible specialisations (Clark, 2014). The presence in the regional economies of these expertise and competencies (which involves considerable levels of information inputs, mental processes and dexterity) creates intrinsically greater value. An explanation of this result could be found in the fact that smart craft workers perform operational activities which embody functions that are traditionally defined as high value-added (for instance, design, prototyping and data analysis). The high value creation along the entire value chain leads to a re-shaping of the smiling curve proposed by Mudambi (2007). We can suggest that, as the value creation associated to the different supply chains' operations converges, the curve becomes flatter and shifts upwards.

6. CONCLUSIONS

Over the last decades, EU labour markets have undergone disruptive changes mainly due to the de-industrialisation process and the adoption of new technologies. The introduction of a wave of new technologies is expected to further disrupt EU labour markets, affecting the regional stock of competences and, thereby, EU job demand. This raises concerns over the sustainability of EU competitiveness longer term.

With this backdrop, the paper highlights that there are combinations of skills that can contribute to increase regional GVA. We find that: i) smart workers contribute to regional

GVA; ii) technicians and professionals have positive complementary added effect on the regional productivity when associated with smart craft workers. These results seem to suggest that production and knowledge-based production-support occupations represent a particularly important driver of productivity. These occupations are an expression of complementary digitally-based competences (such as competences on analytics, data architecture, machine learning, coding and human-machine interaction) and experience-based skills (embedded in craftsmanship talents) critical in the emerging industrial mix. An example related to the footwear industry can illustrate, for instance, how the co-presence of technicians and smart craft workers could be of importance for regional productivity. In order to satisfy the increasing demand of unique, bespoke products (that might transit both onto the mass customisation trend and luxury production), ideals of craft production should be expressed through modern industrial technologies (Boër et al., 2004). Indeed, even though shoemaking production is becoming increasingly automated and digitally-enabled (which requires the employment of specific digital skills), some functions still remain strictly the domain of specific human skills (Boër et al., 2004; Bettiol and Micelli, 2014), such as creativity or experience-based knowledge (for example, the expertise of distinguishing types and quality of leathers). Therefore, there is the need of a symbiotic and mutually constructive collaboration between computer engineers (who do not necessarily have to belong to the footwear sector, but who have to be able to deal with – amongst others – the development of versatile, multi-purpose shoe machines and systems, as well as the data transmission from the physical and virtual sales centres to the manufacturers - Fornasiero et al., 2004; Viganò et al., 2004) and shoemakers (who can actually realise the customised product using their artisanal experienced-based expertise in designing the product, choosing the leather, cutting it and assembling all required components).

In line with the Europe 2020 Agenda, growth needs to be smart to leverage technology and innovation, as well as inclusive by seeking to foster employment leading to socio-territorial cohesion. Our findings seem to suggest that the infusion of new technologies (Martin and Sunley, 2006: 423) in manufacturing and production-support service sectors can provide regions with an opportunity to upgrade and enhance their industrial base. Given the portability of the knowledge domains related to technologies, regions would increase the possibility to recombine different pieces of complementary knowledge (Frenken et al., 2007; Hidalgo et al., 2007) fostering their resilience to technological and market shocks.

The definition of smart workers proposed in the present paper represents a first step towards unpacking a sort of 'skill chain' that includes skill sets associated with emerging - yet overlooked - trends in the manufacturing and service sectors. This definition contributes to the debate in the regional studies and economic geography literature by providing a systematic analysis of the recent impact of disruptive changes (in offshoring trends, technologies and final demand) on the regional skill base and its sustainability. By evidencing a connection between smart workers and regional productivity, this research finds that regions achieve greater productivity if they are endowed with production and knowledge-based production-support workers linked to the emerging manufacturing model, Industry 4.0.

To promote productivity, normatively manufacturing regions should skill up their labour pool to leverage the opportunity technological change and the new manufacturing model. This means combining more traditional talents linked to the embedded industrial competences - craft workers - with workers equipped with talents in digital technologies (Martynovich and Lundquist, 2015). The presence of a smart workforce pool seems to generate both production and consumption externalities (Broersma et al., 2016), that can be defined as the social rate of return on the specialised technical skill, respectively, of workers and of inhabitants in a particular area. For these reasons, regions should build on their industrial legacy by pre-empting the skill atrophy (Bailey and de Ruyter, 2015) of manufacturing know-how and by topping them up with talents in new technologies. The challenge is then how to (re)create a supply of competences that reflects the regional industrial endowment and connects them with new and emerging technologies. Creating this *smart* skill mix might be problematic for regions that have experienced decades of manufacturing hollowing out leading to a shortage of workers with middle-level technical skills (Christopherson, 2011). To boost the development of smart workers across European regions, policy should act on three levels: i) to implement technical, vocational training programmes and higher-education programmes for younger generations to develop new skill sets; ii) to re-train and skill up people in work as the skills in jobs change to avoid joblessness; and iii) to facilitate cross-skills networking to create and support the *makers'* talent to complement science, technology, engineering and digital skills "on companies' shop floors" and across the regional economies. Skills and occupational mix should, therefore, be part of an industrial strategy that aims to support manufacturing sectors across the EU regions by leveraging technological change and the new manufacturing model with an adequate pool of skills.

This study is naturally subject to limitations that offer additional opportunities for future research. More specifically, the present article proposes a first step towards the impact of smart regional productivity. We started exploring this relationship at NUTS-II level, but a finer grained study could be looking at travel-to-work areas or provinces to understand urban-rural difference for instance. On a more macro-level, we hope our contribution helps pave the way for more studies that might explore how different national institutional contexts impact on labour markets and, in turn, on their occupational mix. We also hope it inspires scholars to further engage in research on how smart workers affect regional productivity across, not only advanced, but also emerging economies. Going beyond regional productivity, an important question for future research would be if and how the presence of smart workers could overcome socioeconomic inequalities of a region and influence inclusion by looking, for instance, at changes in GDP growth and/or GDP per head.

REFERENCES

Acemoglu, D. 2002. Technical change, inequality, and the labor market. *Journal of Economic Literature,* 40**,** 7-72.

Acemoglu, D. & Autor, D. 2011. Skills, tasks and technologies: Implications for employment and earnings. *In:* ASHENFELTER, O. & CARD, D. (eds.) *Handbook of labor economics.* Amsterdam: Elsevier.

Amison, P. & Bailey, D. 2014. Phoenix industries and open innovation? The Midlands advanced automotive manufacturing and engineering industry. *Cambridge Journal of Regions, Economy and Society,* 7**,** 397-411.

Anderson, C. 2012. *Makers: The new industrial revolution*, New York, Crown Business.

Annunziata, M. & Biller, S. 2014. The Future of Work. General Electric Discussion Paper.

Artis, M. J., Miguelez, E. & Moreno, R. 2011. Agglomeration economies and regional intangible assets: an empirical investigation. *Journal of Economic Geography,* 12**,** 1167-1189.

Attaran, M. 1986. Industrial diversity and economic performance in US areas. *The Annals of Regional Science,* 20**,** 44-54.

Autor, D. H. 2015. Why are there still so many jobs? The history and future of workplace automation. *The Journal of Economic Perspectives,* 29**,** 3-30.

Autor, D. H. & Dorn, D. 2013. The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review,* 103**,** 1553-97.

Autor, D. H., Levy, F. & Murnane, R. J. 2003. The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics,* 118**,** 1279-1333.

Bailey, D., Bellandi, M., Caloffi, A. & De Propris, L. 2010. Place-renewing leadership: trajectories of change for mature manufacturing regions in Europe. *Policy studies,* 31**,** 457-474.

Bailey, D., Chapain, C. & de Ruyter, A. 2012. Employment outcomes and plant closure in a post-industrial city: an analysis of the labour market status of MG Rover workers three years on. *Urban Studies,* 49**,** 1595-1612.

Bailey, D. & De Propris, L. 2014. Manufacturing reshoring and its limits: the UK automotive case. *Cambridge Journal of Regions, Economy and Society***,** rsu019.

Bailey, D. & de Ruyter, A. 2015. Plant closures, precariousness and policy responses: Revisiting MG Rover 10 years on. *Policy Studies,* 36**,** 363-383.

Baldwin, R. & Robert-Nicoud, F. 2007. Offshoring: General equilibrium effects on wages, production and trade. National Bureau of Economic Research.

Becker, S. O., Ekholm, K. & Muendler, M.-A. 2013. Offshoring and the onshore composition of tasks and skills. *Journal of International Economics,* 90**,** 91-106.

Bellandi, M., De Propris, L. & Santini, E. 2017. Endogenous rerouting and longevity in systemic organisations of production. *In:* MIMEO (ed.).

Berger, R. 2014. *Industry 4.0 - The new industrial revolution. How Europe will success.* [Online]. Available: https://www.rolandberger.com/en/Publications/pub_industry_4_0_the_new_industrial_revolution.html [Accessed 20/11/2017].

Berger, S. 2013. *Making in America: from innovation to market*, Mit Press.

Bettiol, M. & Micelli, S. 2014. The hidden side of design: The relevance of artisanship. *Design Issues - The MIT Press,* 30**,** 7-18.

Blinder, A. S. 2009a. How many US jobs might be offshorable? *World Economics,* 10**,** 41.

Blinder, A. S. 2009b. Offshoring: big deal, or business as usual? *In:* BHAGWATI, J., BLINDER, A. S. & FRIEDMAN, B. M. (eds.) *Friedman Offshoring of American Jobs: What Response from U.S. Economic Policy?* : MIT Press

Boër, C. R., Dulio, S. & Jovane, F. 2004. Editorial: Shoe design and manufacturing. *International Journal of Computer Integrated Manufacturing,* 17**,** 577-582.
Boschma, R. 2015. Towards an evolutionary perspective on regional resilience. *Regional Studies,* 49**,** 733-751.
Boschma, R., Eriksson, R. H. & Lindgren, U. 2014. Labour market externalities and regional growth in Sweden: The importance of labour mobility between skill-related industries. *Regional Studies,* 48**,** 1669-1690.
Boschma, R. & Iammarino, S. 2009. Related variety, trade linkages, and regional growth in Italy. *Economic geography,* 85**,** 289-311.
Boschma, R. & Lambooy, J. 1999. The prospects of an adjustment policy based on collective learning in old industrial regions. *GeoJournal,* 49**,** 391-399.
Bresnahan, T. F. & Trajtenberg, M. 1995. General purpose technologies 'Engines of growth'? *Journal of Econometrics,* 65**,** 83-108.
Broersma, L., Edzes, A. J. & Van Dijk, J. 2016. Human Capital Externalities: Effects for Low-Educated Workers and Low-Skilled Jobs. *Regional Studies,* 50**,** 1675-1687.
Bronzini, R. & Piselli, P. 2009. Determinants of long-run regional productivity with geographical spillovers: The role of R&D, human capital and public infrastructure. *Regional Science and Urban Economics,* 39**,** 187-199.
Buciuni, G., Corò, G. & Micelli, S. 2014. Rethinking the role of manufacturing in global value chains: an international comparative study in the furniture industry. *Industrial and Corporate Change,* 23**,** 967-996.
Casado-Díaz, J. M. 2000. Local Labour Market Areas in Spain: A Case Study. *Regional Studies,* 34**,** 843-856.
Cedefop. 2015. *Skills obsolescence (%) across countries in 2014* [Online]. Available: http://skillspanorama.cedefop.europa.eu/en/indicators/skills-obsolescence [Accessed].
Chennells, L. & Reenen, J. V. 1999. Has technology hurt less skilled workers? A survey of the micro-econometric evidence. IFS Working Papers.
Christopherson, S. 2009. Manufacturing: up from the ashes, Democracy, 14,(Fall).
Christopherson, S. 2011. Riding the small wave in manufacturing to more good jobs and a more diverse economy. *Big Ideas for Job Creation in a Jobless Recovery*.
Christopherson, S. & Clark, J. 2007. *Remaking regional economies: Power, labor, and firm strategies in the knowledge economy*, Routledge.
Christopherson, S., Michie, J. & Tyler, P. 2010. Regional resilience: theoretical and empirical perspectives. *Cambridge journal of regions, economy and society,* 3**,** 3-10.
Clark, J. 2014. Manufacturing by design: the rise of regional intermediaries and the re-emergence of collective action. *Cambridge Journal of Regions, Economy and Society,* 7**,** 433-448.
Clark, J., Huang, H.-I. & Walsh, J. P. 2010. A typology of 'innovation districts': what it means for regional resilience. *Cambridge Journal of Regions, Economy and Society,* 3**,** 121-137.
Crinò, R. 2009. Offshoring, multinationals and labour market: a review of the empirical literature. *Journal of Economic Surveys,* 23**,** 197-249.
Dauth, W. & Suedekum, J. 2015. Globalization and local profiles of economic growth and industrial change. *Journal of Economic Geography,* 16**,** 1007-1034.
Deloitte. 2015. *Industry 4.0. Challenges and solutions for the digital transformation and use of exponential technologies* [Online]. Available: https://www2.deloitte.com/ch/en/pages/manufacturing/articles/manufacturing-study-industry-4.html [Accessed 20/11/2017].
Di Liberto, A. 2008. Education and Italian regional development. *Economics of Education Review,* 27**,** 94-107.

Diodato, D. & Weterings, A. B. 2015. The resilience of regional labour markets to economic shocks: Exploring the role of interactions among firms and workers. *Journal of Economic Geography,* 15**,** 723-742.
Dustmann, C., Fabbri, F. & Preston, I. 2005. The impact of immigration on the British labour market. *The Economic Journal,* 115.
EUROSTAT. 2015. *Manufacturing statistics - NACE Rev. 2* [Online]. Available: http://ec.europa.eu/eurostat/statistics-explained/index.php/Manufacturing_statistics_-_NACE_Rev._2#Further_Eurostat_information [Accessed].
Falk, M. & Koebel, B. M. 2002. Outsourcing, imports and labour demand. *The Scandinavian Journal of Economics,* 104**,** 567-586.
Feenstra, R. C. 2010. Offshoring in the Global Economy: Theory and Evidence. MIT Press.
Florida, R. 2014. *The Rise of the Creative Class--Revisited: Revised and Expanded*, Basic books.
Fornasiero, R., Zangiacomi, A. & Avai, A. 2004. Web cost simulation service for footwear sector. *International Journal of Computer Integrated Manufacturing,* 17**,** 661-667.
Frenken, K., Cefis, E. & Stam, E. 2015. Industrial dynamics and clusters: a survey. *Regional Studies,* 49**,** 10-27.
Frenken, K., Van Oort, F. & Verburg, T. 2007. Related variety, unrelated variety and regional economic growth. *Regional studies,* 41**,** 685-697.
Gabe, T. M. & Abel, J. R. 2015. Shared knowledge and the coagglomeration of occupations. *Regional Studies***,** 1-14.
Gagliardi, L., Iammarino, S. & Rodríguez-Pose, A. 2015. Offshoring and the geography of jobs in Great Britain. *UK Spatial Economics Research Centre - SERC DISCUSSION PAPER 185*.
Gereffi, G., Humphrey, J. & Kaplinsky, R. 2001. Introduction: Globalisation, value chains and development. *IDS bulletin,* 32**,** 1-8.
Glaeser, E. L. 2005. Reinventing Boston: 1630–2003. *Journal of Economic Geography,* 5**,** 119-153.
Goos, M. & Manning, A. 2007. Lousy and lovely jobs: The rising polarization of work in Britain. *The review of economics and statistics,* 89**,** 118-133.
Goos, M., Manning, A. & Salomons, A. 2008. Recent changes in the European employment structure: the roles of technology, globalization and institutions. Katholieke Universiteit Leuven.
Goos, M., Manning, A. & Salomons, A. 2009. Job polarization in Europe. *The American Economic Review,* 99**,** 58-63.
Grossman, G. & Rossi-Hansberg, E. 2008. Trading Tasks: A Simple Theory of Offshoring. *American Economic Review*, 98**,** 1978–1997.
Hidalgo, C. A., Klinger, B., Barabási, A.-L. & Hausmann, R. 2007. The product space conditions the development of nations. *Science,* 317**,** 482-487.
Hijzen, A., Görg, H. & Hine, R. C. 2005. International Outsourcing and the Skill Structure of Labour Demand in the United Kingdom*. *The Economic Journal,* 115**,** 860-878.
Iammarino, S. & McCann, P. 2013. *Multinationals and economic geography: Location, technology and innovation,* Cheltenham UK and Northampton (MA) USA, Edward Elgar Publishing.
Jacquemin, A. P. & Berry, C. H. 1979. Entropy measure of diversification and corporate growth. *The Journal of Industrial Economics***,** 359-369.
Jensen, J. B. & Kletzer, L. G. 2010. Measuring tradable services and the task content of offshorable services jobs. *Labor in the new economy.* University of Chicago Press.

Johansson, B. & Klaesson, J. 2011. Creative milieus in the Stockholm region. *In:* ANDERSSON, D. E., ANDERSSON, A. E. & MELLANDER, C. (eds.) *Handbook of creative cities.*

Jones, R. W. & Kierzkowski, H. 1990. The role of services in production and international trade: a theoretical framework. *In:* JONES, R. W. & KRUEGER, A. O. (eds.) *The Political Economy of International Trade: Essays in Honor of Robert E. Baldwin.* Oxford and Cambridge, Mass.: Blackwell.

Kasabov, E. & Sundaram, U. 2016. Conceptualizing Clusters as Dynamic and Path-Dependent Pools of Skills. *Regional Studies,* 50**,** 1520-1536.

Katz, L. F. & Autor, D. H. 1999. Changes in the wage structure and earnings inequality. *In:* ASHENFELTER, O. & CARD, D. E. (eds.) *Handbook of labor economics.* Amsterdam: Elsevier Science.

Kemeny, T. & Rigby, D. 2012. Trading away what kind of jobs? Globalization, trade and tasks in the US economy. *Review of World Economics,* 148**,** 1-16.

Kennedy, P. 2003. *A guide to econometrics,* Cambridge, MA, MIT press.

Kiel, D., Arnold, C. & Voigt, K.-I. 2017. The influence of the Industrial Internet of Things on business models of established manufacturing companies–A business level perspective. *Technovation,* 68**,** 4-19.

Kohler, W. 2009. Offshoring: why do stories differ? *In:* TONDL, G. (ed.) *The EU and Emerging Markets.* Vienna and New York: European Community Studies Association of Austria Publication Series. Springer.

Lafuente, E., Vaillant, Y. & Vendrell-Herrero, F. 2016. Territorial Servitization: Exploring the virtuous circle connecting knowledge-intensive services and new manufacturing businesses. *International Journal of Production Economics*.

Levy, F. & Murnane, R. J. 2012. *The new division of labor: How computers are creating the next job market,* Princeton University Press.

Lisciandra, M. & Millemaci, E. 2017. The economic effect of corruption in Italy: a regional panel analysis. *Regional Studies,* 51**,** 1387-1398.

López-Bazo, E. & Motellón, E. 2012. Human capital and regional wage gaps. *Regional Studies,* 46**,** 1347-1365.

Lowe, N. J. & Wolf-Powers, L. 2018. Who works in a working region? Inclusive innovation in the new manufacturing economy. *Regional Studies,* 52**,** 828-839.

Lucas, R. B. 1988. On the mechanics of economic development. *Journal of Monetary Economics,* 22 3-42.

Luthi, E. & Schmidheiny, K. 2013. The effect of agglomeration size on local taxes. *Journal of Economic Geography,* 14**,** 265-287.

Lyons, D. 1995. Agglomeration economies among high technology firms in advanced production areas: the case of Denver/Boulder. *Regional Studies,* 29**,** 265-278.

Manca, F. 2012. Human capital composition and economic growth at the regional level. *Regional Studies,* 46**,** 1367-1388.

Markusen, J. 2005. Modeling the offshoring of white-collar services: from comparative advantage to the new theories of trade and FDI. *In:* BRAINARD, L. & COLLINS, S. M. (eds.) *Offshoring White-Collar Work – The Issues and the Implications.* Washington, DC: Brookings Trade Forum.

Martin, R. & Sunley, P. 2006. Path dependence and regional economic evolution. *Journal of economic geography,* 6**,** 395-437.

Martynovich, M. & Lundquist, K.-J. 2015. Technological Change and Geographical Reallocation of Labour: On the Role of Leading Industries. *Regional Studies***,** 1-15.

Morrison Paul, C. J. & Siegel, D. S. 2001. The impacts of technology, trade and outsourcing on employment and labor composition. *The Scandinavian Journal of Economics,* 103**,** 241-264.

Mortensen, D. T. & Pissarides, C. A. 1998. Technological progress, job creation, and job destruction. *Review of Economic dynamics,* 1**,** 733-753.

Mudambi, R. 2007. Offshoring: economic geography and the multinational firm. *Journal of International Business Studies,* 38**,** 206.

Nedelkoska, L. & Neffke, F. 2010. Human capital mismatches along the career path. Jena economic research papers.

Nedelkoska, L., Neffke, F. & Wiederhold, S. Skill mismatch and the costs of job displacement. Annual Meeting of the American Economic Association, 2015.

Neffke, F., Hartog, M., Boschma, R. & Henning, M. 2018. Agents of structural change: the role of firms and entrepreneurs in regional diversification. *Economic Geography,* 94**,** 23-48.

Neffke, F. & Henning, M. 2013. Skill relatedness and firm diversification. *Strategic Management Journal*, 34**,** 297-316.

Neffke, F., Henning, M. & Boschma, R. 2011. How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography,* 87**,** 237-265.

OECD 2017. The Next Production Revolution: Implications for Governments and Business. *OECD Publishing*

. Paris.

Pfeiffer, S. & Suphan, A. 2015. The labouring capacity index: Living labouring capacity and experience as resources on the road to industry 4.0. *Working Paper.* University of Hohenheim.

Pisano, G. P. & Shih, W. C. 2012. Does America really need manufacturing? *Harvard Business Review,* 90**,** 94-+.

Porter, M. E. 1985. *Competitive AdvantageFree Press*.

Porter, M. E. & Heppelmann, J. E. 2014. How smart, connected products are transforming competition. *Harvard Business Review,* 92**,** 64-88.

PwC 2016. Workforce of the future. The competing forces shaping 2030.

Rifkin, J. 2013. *The third industrial revolution: How lateral power is transforming energy, the economy, and the world,* New York, Palgrave-MacMillan, Basingstoke.

Robert-Nicoud, F. 2008. Offshoring of routine tasks and (de) industrialisation: Threat or opportunity—And for whom? *Journal of urban Economics,* 63**,** 517-535.

Romer, P. M. 1990. Endogenous technological change. *Journal of political Economy,* 98**,** S71-S102.

Rueda-Cantuche, M., J., Sousa, N., Andreoni, V. & Arto, I. 2012. The Single Market as an engine for employment growth through the external trade. Seville: Joint Research centre, IPTS.

Sennett, R. 2008. The Craftsman, New Heaven. London, Yale University Press.

Simmie, J. & Martin, R. 2010. The economic resilience of regions: towards an evolutionary approach. *Cambridge journal of regions, economy and society,* 3**,** 27-43.

Skills Panorama. 2016. *Focus on Skills challenges in Europe* [Online]. Available: http://skillspanorama.cedefop.europa.eu/en/analytical_highligths/focus-skills-challenges-europe [Accessed].

Song, J., Almeida, P. & Wu, G. 2003. Learning–by–Hiring: When is mobility more likely to facilitate interfirm knowledge transfer? *Management science,* 49**,** 351-365.

Spitz-Oener, A. 2006. Technical change, job tasks, and rising educational demands: looking outside the wage structure. *Journal of Labor Economics,* 24**,** 235-270.
Stock, J. H. & Yogo, M. 2002. Testing for weak instruments in linear IV regression. National Bureau of Economic Research Cambridge, Mass., USA.
Treado, C. D. 2010. Pittsburgh's evolving steel legacy and the steel technology cluster. *Cambridge journal of regions, economy and society,* 3**,** 105-120.
Viganò, G., Mottura, S., Greci, L., Sacco, M. & Boër, C. R. 2004. Virtual reality as a support tool in the shoe life cycle. *International Journal of Computer Integrated Manufacturing,* 17**,** 653-660.
Wiegmann, P. M., de Vries, H. J. & Blind, K. 2017. Multi-mode standardisation: A critical review and a research agenda. *Research Policy,* 46**,** 1370-1386.
Wixe, S. 2015. The impact of spatial externalities: Skills, education and plant productivity. *Regional Studies,* 49**,** 2053-2069.
Wolf-Powers, L., Doussard, M., Schrock, G., Heying, C., Eisenburger, M. & Marotta, S. 2017. The Maker Movement and Urban Economic Development. *Journal of the American Planning Association***,** 1-12.
World Economic Forum 2016. The future of jobs: Employment, skills and workforce strategy for the fourth industrial revolution. Geneva, Switzerland: World Economic Forum.
Wosnitza, B. & Walker, M. 2008. Regional economic indicators May 2008 with a focus on differences in sub-regional economic performances. *The Labour gazette,* 2**,** 40-53.
Wright, R., Ellis, M. & Townley, M. 2017. The Matching of STEM Degree Holders with STEM Occupations in Large Metropolitan Labor Markets in the United States. *Economic Geography,* 93**,** 185-201.
ZongWei, L. (ed.) 2014. *Smart Manufacturing Innovation and Transformation: Interconnection and Intelligence,* Hershey, PA, USA: IGI Global.

TABLES

Table 1. Definitions of variables used in the empirical analysis at NUTS-II level

Variable	Description	Source
Gross Value Added (GVA) per employee	Natural logarithm of Gross Value Added at basic prices in the region *r* at time *t* [nama_10r_3gva] over employment (thousand persons) in the region *r* at time *t* [nama_10r_3empers]	EUROSTAT
Managers	Share of managers (category 1 in ISCO-08) over the total workforce[14] in the region *r* at time *t*	Microdata EU-LFS (EUROSTAT)
Professionals	Share of professionals (category 2 in ISCO-08) over the total workforce in the region *r* at time *t*	Microdata EU-LFS (EUROSTAT)
Technicians	Share of technicians and associate professionals (category 3 in ISCO-08) over the total workforce in the region *r* at time *t*	Microdata EU-LFS (EUROSTAT)
Clerical support workers	Share of clerical support workers (category 4 in ISCO-08) over the total workforce in the region *r* at time *t*	Microdata EU-LFS (EUROSTAT)
Services and sales workers	Share of services and sales workers (category 5 in ISCO-08) over the total workforce in the region *r* at time *t*	Microdata EU-LFS (EUROSTAT)
Craft workers	Share of craft and related trades workers (category 7 in ISCO-08) over the total workforce in the region *r* at time *t*	Microdata EU-LFS (EUROSTAT)
Plant workers	Share of plant and machine operators and assemblers (category 8 in ISCO-08) over the total workforce in the region *r* at time *t*	Microdata EU-LFS (EUROSTAT)
Smart workers	Share of occupations linked to advanced manufacturing sector (see appendix A***)*** over the total workforce in the region *r* at time *t*	Microdata EU-LFS (EUROSTAT)
Smart workers* Smart workers	Smart workers minus the mean of smart workers (at the country level at time *t*) to the power two in the region *r* at time *t*[15]	Microdata EU-LFS (EUROSTAT)
Smart craft workers	Dummy variable, value 1 if the share of smart craft workers (category 72, 73, 752, 753 in ISCO-08, see appendix A) over the total workforce in the region *r* at time *t* is equal or above the 25th percentile	Microdata EU-LFS (EUROSTAT)
Industrial diversity	Measure of the distribution of the employees (thousand persons) across economic activity (NACE Rev. 2) in the region *r* at time *t* [nama_10r_3empers]	Microdata EU-LFS (EUROSTAT)
R&D investments	Natural logarithm of total (all sector) intramural R&D expenditure (GERD in million Euros) of performance [rd_e_gerdreg] in the region *r* with three-year lag[16]	EUROSTAT

[14] The total number of employed persons includes: managers, professionals, technicians and associate professionals, clerical support workers, service and sales workers, skilled agricultural and fishery workers, craft and related trades workers, plant and machine operators, and assemblers and elementary occupations. We did not consider armed force workers.
[15] The reason behind the use of mean is that multicollinearity between a predictor variable and its nonlinear term disappears when the predictors are centred (i.e., subtracting its mean) before forming the power term. (Moosbrugger et al., 2009).
16 In order to take into consideration the lag between R&D expenditure and the productivity impact it may cause, we use the variable R&D expenditure lagged. In previous studies, three to five-year lags are generally used (Acs and Audretsch, 1991). We used a three-year lag as this window lag generates a more robust model (in terms of coefficient magnitude, statistical significance and standard errors). Results are available from the authors upon request.

Table 2. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Occupations					
Managers	564	0.05	0.02	0.01	0.14
Professionals	564	0.16	0.04	0.10	0.33
Technicians	564	0.17	0.05	0.04	0.26
Service and sales workers	564	0.18	0.04	0.11	0.37
Clerical support workers	564	0.11	0.02	0.05	0.18
Plant workers	564	0.07	0.02	0.01	0.13
Smart workers	564	0.15	0.04	0.01	0.25
Smart craft workers	564	0.05	0.02	0.00	0.13
Technicians*Smart craft workers	564	0.01	0.01	0.00	0.02
Professionals*Smart craft workers	564	0.01	0.00	0.00	0.02
Regional characteristics					
GVA per employee (ln)	564	4.06	0.22	3.39	4.61
Industrial diversity	564	2.55	0.10	2.10	2.76
R&D investments (ln)	564	6.21	1.62	0.22	9.82

Table 3. Correlation matrix

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14
GVA per employee (ln)	(1)	1.0000													
Managers	(2)	0.4497*	1.0000												
Professionals	(3)	0.4832*	0.4839*	1.0000											
Technicians	(4)	0.5388*	0.0396*	0.0238	1.0000										
Service and sales workers	(5)	0.3797*	0.1821*	0.0991*	0.6405*	1.0000									
Clerical support workers	(6)	0.2621*	0.0269	0.0141	0.4608*	0.4958*	1.0000								
Plant workers	(7)	0.0040	0.2233*	0.2816*	0.0806*	0.0177	0.3820*	1.0000							
Smart workers	(8)	0.4937*	0.0737*	0.0141	0.7132*	0.6439*	0.2926*	0.3053*	1.0000						
Smart workers*Smart workers	(9)	0.0588*	0.0948*	-0.0127	0.1167*	0.1665*	0.0681*	0.0449*	0.0461*	1.0000					
Smart craft workers	(10)	-0.0170	0.4299*	0.4122*	0.3543*	0.3724*	0.2406*	0.3079*	0.7180*	0.0886*	1.0000				
Technicians*Smart craft workers	(11)	0.1796*	0.3491*	0.3138*	0.7048*	0.5577*	0.4081*	0.1473*	0.8217*	0.0219	0.8944*	1.0000			
Professionals*Smart craft workers	(12)	0.2066*	0.2509*	0.1076*	0.3655*	0.4335*	0.2436*	0.2268*	0.7620*	0.0734*	0.8239*	0.7582*	1.0000		
Industrial diversity	(13)	0.4031*	0.2133*	0.2087*	0.2194*	0.0757*	0.1781*	0.0588*	0.0752*	0.2034*	0.1989*	0.1308*	0.1148*	1.0000	
R&D investments (ln)	(14)	0.5580*	0.1648*	0.3130*	0.6153*	0.5598*	0.3179*	0.0168	0.6452*	0.1494*	0.2085*	0.4056*	0.3977*	0.4194*	1.0000

Table 4. Estimated impact of occupational mix and regional characteristics

Dependent variable	GVA per employee (ln)											
	Smart workers										Smart Workers Non-Linear Effect	
Estimator	Pooled OLS		FE		GMM						FE	
	[1]	[2]	[3]	[4]	[5] First stage	[5] Second stage	[6] First stage	[6] Second stage	[7] First stage	[7] Second stage	[8]	[9]
Occupations												
Managers	3.39***	3.05***	0.07	0.14	-0.71***	7.07***	-0.65***	7.57***	-0.68***	8.03***	0.06	0.14
	(0.62)	(0.57)	(0.12)	(0.12)	(0.08)	(0.79)	(0.08)	(0.88)	(0.07)	(1.09)	(0.12)	(0.12)
Service and sales workers	-0.33	-0.04	0.01	0.12*	-0.70***	2.00**	-0.70***	2.62**	-0.74***	2.79**	0.01	0.13*
	(0.33)	(0.34)	(0.07)	(0.07)	(0.04)	(0.80)	(0.05)	(0.90)	(0.05)	(1.12)	(0.07)	(0.07)
Clerical support workers	3.22***	3.05***	0.03	0.07	-0.25***	0.87**	-0.35***	1.18**	-0.39***	1.23**	0.03	0.09
	(0.51)	(0.48)	(0.10)	(0.10)	(0.07)	(0.40)	(0.07)	(0.50)	(0.06)	(0.62)	(0.10)	(0.10)
Smart workers	1.08***	0.90**	0.22**	0.23**		4.70***		4.57***		5.20***	0.22**	0.23**
	(0.29)	(0.35)	(0.09)	(0.08)		(0.98)		(1.15)		(1.38)	(0.09)	(0.08)
Smart workers*Smart workers											0.45	1.27
											(0.90)	(0.93)
High tech patent applications					0.01***							
					(0.01)							
Computer and automated business equipment patent applications							0.01***					
							(0.00)					
Communication technology patent applications									0.01***			
									(0.01)			
Regional characteristics												
Industrial diversity		0.01		0.10	0.01	0.45***	-0.03	0.36***	-0.04	0.44***		0.10
		(0.12)		(0.06)	(0.02)	(0.11)	(0.02)	(0.11)	(0.02)	(0.12)		(0.07)
R&D investments (ln)		0.02*		0.03**								0.03**
		(0.01)		(0.01)								(0.01)
Controls												
Country dummies (8)	Yes	Yes	Yes	Yes							Yes	Yes
Time dummies (4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.51***	3.40***	4.00***	3.52***	0.34***	1.34**	0.44***	1.45**	0.46***	1.08	4.00***	3.50***
	(0.12)	(0.34)	(0.02)	(0.19)	(0.05)	(0.40)	(0.06)	(0.55)	(0.06)	(0.67)	(0.02)	(0.19)
Number of obs.	564	564	564	564	503	503	426	426	447	447	564	564
Goodness of fit												
R^2	0.85	0.86	0.29	0.33	0.50	0.43	0.49	0.31	0.49	0.29	0.29	0.33
Prob>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap rk LM statistic (Underidentification test)						22.97		20.94		18.01		
Chi-sq(1) P-val (Underidentification test)						0.00		0.00		0.00		
Cragg-Donald Wald F statistic (Weak identification test|)						33.39		26.18		25.99		
Kleibergen-Paap rk Wald F statistic						30.90		27.25		35.89		

Notes: Robust standard errors are clustered on 141 labour market regions. Robust standard errors are given in parentheses. ***Parameter estimate is statistically significant at the 1% significance level; **parameter estimate is statistically significant at the 5% significance level; *parameter estimate is statistically significant at the 10% significance level. R^2 in FE models is within groups. Estimations in GMM models are performed with ivreg2 package (Baum, Schaffer and Stillman, 2010). ivreg2: Stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML and k-class regression. http://ideas.repec.org/c/boc/bocode/s425401.html). Kleibergen-Paap rk Wald F statistic is the LM statistics testing for under-identification.

Table 5. Estimated impact of occupational mix and regional characteristics

Dependent variable	GVA per employee (ln)			
	Co-presence of technicians and smart craft workers		Co-presence of professionals and smart craft workers	
Estimator	FE		FE	
	[10]	[11]	[12]	[13]
Occupations				
Managers	0.17	0.21	0.17	0.26*
	(0.13)	(0.13)	(0.13)	(0.14)
Service and sales workers	0.16*	0.21**	0.16*	0.19**
	(0.09)	(0.09)	(0.09)	(0.09)
Clerical support workers	0.04	0.08	0.04	0.07
	(0.11)	(0.10)	(0.11)	(0.10)
Professionals	-0.07	-0.01	-0.07	-0.14*
	(0.07)	(0.07)	(0.07)	(0.07)
Technicians	0.13	0.05	0.13	0.19*
	(0.11)	(0.10)	(0.10)	(0.11)
Plant operator	0.15	0.23	0.15	0.19
	(0.22)	(0.20)	(0.22)	(0.21)
Technicians*Smart craft workers		3.02**		
		(0.90)		
Professionals*Smart craft workers				3.66**
				(1.37)
Regional characteristics				
Industrial diversity	0.10	0.11*	0.10	0.12*
	(0.06)	(0.06)	(0.06)	(0.06)
R&D investments (ln)	0.03**	0.03**	0.03**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
Controls				
Country dummies (8)	Yes	Yes	Yes	Yes
Time dummies (4)	Yes	Yes	Yes	Yes
Constant	3.54***	3.45***	3.54***	3.43***
	(0.19)	(0.20)	(0.19)	(0.20)
Number of obs.	564	564	564	564
Goodness of fit				
R^2	0.33	0.35	0.33	0.35
Prob>F	0.00	0.00	0.00	0.00

Notes: Robust standard errors are clustered on 141 labour market regions. Robust standard errors are given in parentheses. ***Parameter estimate is statistically significant at the 1% significance level; **parameter estimate is statistically significant at the 5% significance level; *parameter estimate is statistically significant at the 10% significance level. R^2 in FE models is within groups.

APPENDIX A

List of smart workers, selected from the International Standard Classification of Occupations (ISCO-08) at 3-digit level.

ISCO-08 Code	Smart workers' sub-category	References*
2 Professionals		
21 Science and engineering professionals		
212 Mathematicians, actuaries and statisticians	Knowledge-based production support	Wright et al. (2017)
213 Life science professionals	Knowledge-based production support	Wright et al. (2017)
214 Engineering professionals (excluding electrotechnology)	Knowledge-based production support	Boschma et al. (2014)
215 Electrotechnology engineers	Knowledge-based production support	Song et al. (2003)
216 Architects, planners, surveyors and designers	Knowledge-based production support	Florida (2014)
25 Information and communications technology professionals		
251 Software and applications developers and analysts	Knowledge-based production support	OECD (2016; 2017)
252 Database and network professionals	Knowledge-based production support	OECD (2016; 2017)
3 Technicians and associate professionals		
31 Science and engineering associate professionals	Knowledge-based production support	
311 Physical and engineering science technicians	Knowledge-based production support	Song et al. (2003)
313 Process control technicians	Knowledge-based production support	Pfeiffer and Suphan (2015)
314 Life science technicians and related associate professionals	Knowledge-based production support	Wright et al. (2017) Response_to_Reviewers_RR3.docx
343 Artistic, cultural and culinary associate professionals	Knowledge-based production support	Florida (2014)
35 Information and communications technicians		
351 Information and communications technology operations and user support technicians	Knowledge-based production support	OECD (2016, 2017)
352 Telecommunications and broadcasting technicians	Knowledge-based production support	OECD (2016, 2017)
7 Craft and related trades workers		
72 Metal, machinery and related trades workers		Berger (2013)
721 Sheet and structural metal workers, moulders and welders, and related workers	Artisan/creative technical knowledge production	
722 Blacksmiths, toolmakers and related trades workers	Artisan/creative technical knowledge production	
723 Machinery mechanics and repairers	Artisan/creative technical knowledge production	
73 Handicraft and printing workers		Bettiol and Micelli (2014), Sennett (2008)
731 Handicraft workers	Artisan/creative technical knowledge production	
732 Printing trades workers	Artisan/creative technical knowledge production	
75 Food processing, wood working, garment and other craft and related trades workers		Hatch (2013), Wolf-Powers et al. (2017)

752 Wood treaters, cabinet-makers and related trades workers	Artisan/creative technical knowledge production	
753 Garment and related trades workers	Artisan/creative technical knowledge production	
8 Plant and machine operators and assemblers		
81 Stationary plant and machine operators		Pisano and Shih (2009; 2012)
813 Chemical and photographic products plant and machine operators	Machine technical knowledge production	
814 Rubber, plastic and paper products machine operators	Machine technical knowledge production	
815 Textile, fur and leather products machine operators	Machine technical knowledge production	
816 Food and related products machine operators	Machine technical knowledge production	
817 Wood processing and papermaking plant operators	Machine technical knowledge production	
818 Other stationary plant and machine operators	Machine technical knowledge production	
82 Assemblers		Pisano and Shih (2009;2012)
821 Assemblers	Machine technical knowledge production	

Note: *Main scholarly contributions from which we built upon to derive the identification of production and knowledge-based production-support occupations expression of digitally-based competences and experience-based skills critical in the emerging industrial mix.