State-of-the-art literature survey

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Abstract

This document contains an extensive literature review of the state-of-the-art related to the research in UNTANGLED work packages (WPs) 3 to 6. The literature covered relates to (a) the impact of the three mega-trends of technological transformations, globalisation and demographic changes, and how they affect labour markets and social outcomes (WPs 3 to 5); and (b) literature related to building scenarios for Europe (WP 6). The document is divided into four sections. Each of the first three sections is concerned with the effect of these trends at the macro (WP3), meso (WP4) or micro (WP5_ societal level. The last section looks at scenario building (WP6). It is a living document in the sense that throughout the project additional sources will be added to keep the literature review up to date.

Keywords: Employment, job quality, skills, income inequality, labour mobility, low-skilled workers, gender, technology, globalisation, demographics

State-of-the-art literature survey

1. Macro level analysis

1.1. Demography, productivity growth, and capital formation[1]

There has been a long tradition of studying the relationship between population age structures and performance. For example, Hansen (1938) argues that population ageing leads to higher savings relative to investment, implicating secular stagnation (see also Summers, 2013; Teulings & Baldwin, 2014). Acemoglu and Restrepo (2018b) provide evidence for a large sample of countries that the growth of GDP per capita is larger for countries experiencing more rapid ageing, and they argue that this could be explained by the more rapid adoption of technologies due to demographic pressures. In particular, they empirically consider 1990 to 2015 and find a positive relationship in many econometric specifications. This is further explained by a strong positive correlation between ageing and the adoption of robots, which is documented in more detail in Acemoglu and Restrepo (2018a). They also provide a theoretical framework with the explanation that labour scarcity encourages automation (see also Acemoglu & Restrepo, 2018b). Focusing on advanced economies, the ordinary least squares (OLS) results for the OECD countries in their sample does not show any significant result of ageing on GDP per capita growth; however, when examining birth rates, the relationship becomes positively significant. Nevertheless, when the period is reduced to 2000 to 2015, the results in Acemoglu and Restrepo (2017) are not significant in any specification for OECD countries.

Maestas *et al.* (2016) investigate this topic across US states and find a negatively significant relationship. Relative to the results reported before, this might be explained by more similar technologies and the adoption of robots (or new technologies), which might explain that the effects argued in Acemoglu and Restrepo (2017) are absent.[2] Methodologically, Maestas *et al.* (2016) start from a production function approach that decomposes the effects into a contribution to labour productivity and labour force growth. They find that a 10% increase in a fraction of the 60+ population impacts negatively on growth by 5.5%, with two-thirds resulting from lower labour productivity growth and one-third from slow labour force growth. In older literature, Lind and Malmberg

[1] The text under this heading is largely taken from Stehrer and Tverdostup (2022) (Deliverable 3.1 of the UNTANGLED project).

[2] The same argument might apply for the sample and results for the OECD countries mentioned before.

(1999) and Feyrer (2007) find that data before 1990 indicates a negative relationship between ageing (measured as the share of population aged above 50) and GDP per capita.

Prettner and Bloom (2020) overview the impact of demographic change on automation, which is also considered a response to the ongoing ageing patterns driven by the decline in fertility rates (as well as declining mortality rates). They hint that a declining dependency ratio (due to declining fertility) implies a rise in GDP per capita (even if productivity defined as GDP per employed person is constant). However, the impacts of declining mortality and increasing life expectancy are strongly dependent on the affected age group. For example, if old-age mortality decreases, there is likely to be a negative impulse on economic growth. Furthermore, indirect effects, such as increasing life expectancy, implies an incentive to invest in learning and education (due to a larger expected pay-off), which has a positive effect on productivity and growth.[3] However, in many advanced economies, increasing dependency ratios evolve with numerous economic, social and political consequences that might be counteracted by various responses (such as more investment in education, government investment in health and education, savings decisions, etc.).

One particular aspect is whether investments and automation could also be mechanisms for reducing the impact of ageing. A simple theoretic growth set-up (assuming a Cobb-Douglas production function) shows that a decline in labour force growth (or a decline in the labour force) results in an incentive to invest more in automation. It descriptively shows that robot density is higher in countries with stronger ageing trends (and vice versa). Abeliansky and Prettner (2017) demonstrate that a 1% decrease in population leads to an increase of 2% in robot density growth rate. Additionally, they discuss how robotisation impacts the replacement of jobs (with estimates between 12 and 65 million workers); however, these numbers are not compared to population projections.[4] Focusing on European economies, Leitner and Stehrer (2019b) calculate long-term GDP and productivity growth rates and trends in participation rates and conclude that, for several countries, demographic developments are likely to kick in and begin jeopardising further growth in the near future. Different simulation exercises demonstrate that in some EU countries, particularly in Central and Eastern Europe, labour supply-side constraints would already materialise in the mid-2020s. In a follow-up paper, (Leitner & Stehrer, 2019a) argue that higher productivity growth is

[3] This is also known as the 'Ben-Porath mechanism'; see Ben-Porath (1967).

[4] In a wider debate, there are also several arguments that fertility decreases with automation, although a few counter-arguments might be given as well.

needed, and the current labour productivity growth rate in the EU needs to more than double to circumvent a negative impact on growth due to a decline in the working-age population. Even though robots exhibit a positive impact on labour productivity growth in their analysis, this is not (yet) strong enough to close the gap between the recent and hypothetical labour productivity trend growth rate that would be required.

1.2. Migration and the supply of skills

This task provides a dynamic analysis of the skill supply in European labour markets by focusing on the composition of workers by origin. It is vital to identify recent trends in skills supplied by foreign workers, who tend to constitute an increasing share of European labour market, because immigrants are unequally distributed across regions, sectors, and occupations, and tend to differ from natives with respect to skills and age. We document the sorting patterns of immigrants across occupations, sectors, and regions, by comparing the allocation of immigrant workers with incumbent natives. Using the current allocation of immigrant and native workers across occupations, and knowing the skill composition of occupations, we identify the skills that under-/oversupplied by foreign workers relative to native workers. This allows assessing the effects of by international labour mobility on skill supply.

First of all, it must be noted that migration flows, especially among skilled workers, can only be fluid if a number of barriers are alleviated at the European level. Zimmermann (2005) points to the European Union's ageing population, the lack of skilled workers, and the high unemployment among low-skilled workers. He argues that a selective migration policy, which would specifically target skilled migrants, would foster growth and generate positive spillovers on all native workers. In order to reach this goal, he identifies two major issues, namely the lack of coordination on migration policies within the EU and the need for competitive institutional settings in order to support European companies' attractiveness on the international labour market (see Kerr *et al.,* 2016 for a review of the global mobility of high-skilled workers). Krause *et al.* (2017) analyse data from online survey among European labour market experts, which confirms that there is a need for 'recognising professional qualifications more efficiently and harmonising social security systems'. The need for a proper recognition of migrants' skills across European countries appears to be a challenge both to the economic success of migrants as well as to the development of harmonised data for research purposes. Winterton (2009) stresses that 'despite initiatives like the European Qualifications Framework there is still no consensus for adopting a common competence model and policy discussions continue to reveal confusion.' The differences in approaches to skill formation are attributed to language and cultural issues. As far as research is concerned, skills per se are generally not measured by regular statistical agencies, and when they are, the lack of uniformisation or the lack of such information on migrants samples explain the scarcity of research on migrant skills. Instead, most studies rely on skill proxies, such as qualifications or the number of years of education.

In light of this, research focused on education shows that migrants' degrees are not properly recognised in host countries. Together with language barriers, the lack of degree recognition generates misallocations of migrant workers. Jestl *et al.* (2015) use Eurostat Labour Force Survey (LFS) to compare the extent of 'job-skill mismatch' between migrants and natives inside the EU. They find that over-education is more prevalent among migrant workers than among natives, especially in low-skill occupations. Visintin *et al.* (2015) also find that skill mismatch is more common among migrants, although the extent of this phenomenon varies across countries of origin and of destination. Brücker *et al.* (2021) exploit survey data merged with German administrative records to study the impact of occupational recognition. They find about 20% wage increases and 25% higher employment probability in the three years that followed recognition, leading migrants to assimilate in terms of wages.

On the impact of migration on native workers, Cattaneo *et al.* (2014) use longitudinal data to assess the impact of migration on natives' career paths. They show that, as the inflow of migrant workers increases, native European workers tend to move to occupations associated with higher skills and status, whereas their probability of unemployment does not increase. Faggian *et al.* (2017) provide a literature review of interregional migration with a focus on how human capital flows impact both receiving and sending economies. They identify two gaps in the literature, namely the relatively low coverage of the impact of migration on sending regions, and more importantly, the limited availability of data on migrant characteristics, especially skills.

Zhang and Lucey (2019) construct a novel brain drain/gain index to analyse the mobility of skilled workers in 30 European countries between 2001 and 2015. They find that a country's level of relative development within Europe affects net flows, with the most developed countries being net recipients of tertiary graduates at the expense of the least developed countries, although some exceptions exist. They also find that the 2008 economic crisis has exacerbated this gap.

The notion that migration flows respond to heterogeneous levels of unemployment and to economic crises within the EU is vastly documented. Arpaia *et al.* (2016) show that from 1970 to 2013, when an asymmetric economic shocks occurs inside the EU, about a quarter of that shock was absorbed within one year thanks to labour mobility. Shock-related movements have almost doubled since the introduction of the euro and have translated into more responsive real wages. Elsner and Zimmermann (2016) find an increase in migration to Germany from countries that were more hardly hit by the Great Recession, but that the magnitude of net flows is insufficient to significantly reduce unemployment in the sending countries. Jauer *et al.* (2018) use regional panel data on pre- and post-crisis migration movements and find similar results for the EU and the US. For the EU, they find that most of the migratory flows are attributed to citizens from countries which recently joined the EU and to third-country nationals. Beine *et al.* (2019) study the impacts of both long term drivers of migration and the short-run economic fluctuations, and find that both types of factors contribute to migration flows. They also show that the Schengen Agreement and the euro currency significantly increased the within-EU worker mobility.

Since every occupation requires a specific mix of skills and abilities, the literature using data on mere education levels can only partially describe the interregional mobility of labour. This is particularly true in the context of migrant workers, since as discussed above, there are issues in the recognition of immigrants' educational attainment. A recent strand of the literature thus goes beyond education levels and attempts to look deeper into workers' and occupations' skills. The O*NET Content Model provides structured information on the characteristics of each occupation, called occupation descriptors. These descriptors are based on a standardised, measurable set of variables obtained from worker surveys. To the best of our knowledge, this type of data has only been used for research on the US. Peri and Sparber (2009) use O*NET and individual US census data to show that migrant workers specialise in occupations requiring physical skills, whereas natives are more allocated to jobs involving communication tasks. Aldaz Odriozola and Eguía Peña (2016) extend the work of Peri and Sparber (2009) by controlling for gender and length of residence. They find that length of stay generates some degree of occupational assimilation among male migrants, whereas female immigrants tend to be confined in a few 'niche jobs'. Sharpe and Bollinger (2020) also use O*NET data and find higher partial equilibrium effects on natives compared to previous research based on education and experience, in particular on the least skilled natives. In contrast, high skill natives benefit from immigration in terms of higher wages.

Beyond higher substitutability among low-skilled workers, a possible explanation of the negative impact on low-skilled natives stems from the fact that many migrants employed in low-skilled jobs tend to achieve professional progress and skills development in sectors whose conditions are usually deemed unattractive (Moroşanu *et al.,* 2021). Finally, Tountopoulou *et al.* (2021) review the literature on international skill frameworks and use survey data to identify key skills for the *labour* market integration of migrant groups. They highlight the importance of (i) hard skills attached to specific tasks and (ii) transversal soft skills. They state that recruiting procedures would benefit from skills profiling and online tools of skill assessment.

1.3. Population ageing, technology and job polarisation[5]

The use of Information and Communication Technologies (ICT) and robots has been changing the world of work in the last few decades. Between 2000 and 2019, the real value of ICT capital per worker in Europe has increased by 91%, while the robot exposure, measured by the number of industrial robots per 1,000 workers, has increased by 140%. Robots and other labour-saving technologies can have important aggregate and compositional labour market effects. They can directly reduce employment as machines replace humans in performing certain tasks, resulting in a labour-saving effect. However, the product demand effect - i.e., an increase in activity thanks to a productivity-enhancing technology - and the demand spillover effect - i.e., demand for other sectors' output resulting from higher value added and incomes in the technology-adopting sector - can increase employment. Gregory, Salomons and Zierahn (2021) showed that the latter two effects have been dominant in Europe, leading to an overall positive employment effect of routine-replacing technologies.

However, computers and other digital technologies have changed the structure of jobs tasks performed by humans, reducing the role of routine tasks and increasing the role of non-routine tasks, both within and across occupations (Autor, Levy & Murnane 2003; Spitz-Oener, 2006). This has led to job and wage polarisation in developed countries (Goos, Manning & Salomons, 2014). This hollowing out of the middle-paid jobs has created winners and losers of technological progress. While a lot of attention has been paid to differences associated with education (Firpo, Fortin &

[5] The text under this heading is largely taken from Albinowski and Lewandowski (2022) of the UNTANGLED project.

Lemieux, 2011; Gathmann & Schönberg, 2010), the age- and gender dimensions of exposure to new technologies have not been comprehensively studied.

There are two main reasons why the effects of technology adoption can differ for younger and older workers. On the one hand, technological change can reduce returns to old skills related to technology that become obsolete, and increase returns to new skills related to emerging technology (Fillmore & Hall, 2021). As older workers tend to have skills that complement older technologies, and their expected returns from an investment in new skills are lower than those of younger workers, the older workers can be more affected by technological change. Indeed, older people (aged 55-64) in the OECD countries tend to have lower ICT and analytical skills and are less likely to use information-processing skills at work than younger individuals (the Programme for the International Assessment of Adult Competencies – PIAAC – data). On the other hand, older workers are more likely to benefit from insider power, and, as such, may be more protected from changes than younger workers, who are often outsiders or labour market entrants. Indeed, there is evidence that the de-routinisation of work in Europe has affected younger workers to a larger extent (Lewandowski *et al.,* 2020), and that industrial robots in Germany have reduced the labour market prospects of younger workers (Dauth *et al.,* 2021).

The issue of differential impact of technological progress and international trade has been studied before for selected countries. Behaghel *et al.* (2014) use French firm-level data from late 1990s. They find that the adoption of ICT innovations reduced the share of workers aged 50–59 in the wage bill. Autor *et al.* (2015) show that US workers aged 40 and above are more likely to drop out of employment when technology replaces routine jobs than it is the case for younger workers. They also observe that negative employment effects associated with the increase in Chinese imports are very similar among younger and older workers. Jerbashian (2019) combines EU-KLEMS and LFS data and analyses impact of the fall in IT prices in 10 European countries over the period 1993-2007. He finds that older workers (above 45) benefited less from the favourable changes in occupational structure, induced by ICT adoption, than younger workers. Lewandowski *et al.* (2020) use EU-LFS data for 12 countries over the period 1998-2015. They analyse the de-routinisation of work and find that older workers were less affected by occupational changes than younger workers.

The gender dimension is also relevant. On one hand, routine-replacing technologies increase returns to social skills which women tend to have a comparative advantage in (Deming, 2017) so they benefit more from ICT adoption than men (Jerbashian, 2019). On the other hand, women lag behind men in skills complementary to new technologies: women are less likely than men to study in Science, Technology, Engineering, and Mathematics (STEM) college programmes (Delaney & Devereux, 2019) and exhibit lower numeracy skills (Rebollo-Sanz & De la Rica, 2020).

1.4. Changing skills

The European labour markets are massively impacted by the three mega trends studied in UNTANGLED (digitalisation, globalisation, demographic changes).

First, the recent changes induced by digitalisation deeply impact firms and workers and the COVID-19 economic crisis is speeding up digitalisation (WEF, 2020). These factors have an impact on the task content of the jobs and the characteristics of job demand (Autor, 2019; Burzyński, 2020). Second, trade shocks induced by globalisation reallocate jobs across business sectors (Autor, Dorn & Hanson, 2013; Guren, Hémous & Olsen, 2015). Third, parallel demographic changes induced notably by population ageing (Schulz & Radvansky, 2014) create new job opportunities. Finally, these trends may reinforce the skills shortage on the labour market.

The aim of the task 3.4 is to map skill similarities across occupations and business sectors as well as the skill speed of change in the last years.

Regarding the classification of skills, the related state-of-the art revolves around two distinct approaches of classifying workers' skills. On the one hand, the first and most popular approach relies on information about tasks performed by workers. This results in the well-known differentiation between routine and non-routine work initiated by Autor *et al.* (2003) and enriched later by Acemoglu and Autor (2011) or Lewandowski *et al.* (2019). In this strand of research, five tasks are often distinguished: (i) routine manual (e.g. picking or sorting, repetitive motions, operating or controlling machines); (ii) routine cognitive (e.g. record-keeping, calculating, bookkeeping, correcting texts or data, measuring length, or weight, or temperature, repetitive customer service), (iii) non-routine manual (e.g. manual dexterity, spatial orientation, repairing or renovating), (iv) non-routine analytical (e.g. forming/testing hypotheses, researching, analysing, evaluating and planning, designing, creativity, problem solving); (v) non-routine interactive (e.g. negotiating, lobbying, coordinating, organising, guiding, directing, motivating, communicating). Some other scholars do not disentangled sub-categories and focus on three tasks: routine, non-routine manual, non-routine cognitive as in Cortes (2016).

On the other hand, international organisations such as Cedefop, or OECD developed their own way of classifying skills. It relies on a distinction between three main skill families: (i) hard skills (e.g. customer services, foreign languages); (ii) soft skills (e.g. planning, team work) (Cedefop, 2017); and sometimes iii) digital skills (Fernández-Macías & Bisello, 2020; OECD, 2016). Both approaches usually use information from databases which are based on worker surveys or expert information, such as the Occupational Information Network (O*NET) or the European Skills, Competences, Qualifications and Occupations (ESCO). A relatively new approach to quantify skill needs is to use word embeddings and network community detection algorithms to extract skills directly for job advertisement (e.g. Djumalieva & Sleeman, 2018).

The extant evidence regarding skill similarities across occupations rely on various type of data coming from surveys, from training curricula, administrative data or job offers (newspapers and/or online). Regarding surveys, Chuang (2020), studying recent data collected in the Vigo County of Indiana, US, provides an estimate of the potential of workers' skills mobility using respondents' perception about the displacement potential of their own skills. His main result is that about half of the respondents were not aware of their risk of skill obsolescence due to technological progress. Dworkin (2019) uses US data collected in 2016 (from the Bureau of Labor Statistics), assesses the skills, knowledge and abilities similarities between each pair of jobs and provides a transition recommendation model in order to ease the job transition of workers impacted by automation. He quantifies the potential benefit of increasing individual skills to facilitating both job transitions and within-occupation skill redefinition.

Geel and Backes-Gellner (2011), applying the Lazear's skill-weights approach (Lazear, 2009) on German survey data (BIBB/BAuA Employment Survey, 2005/06), identify clusters of occupations characterised by similar skill combinations and reveal that the probability of changing occupations is higher within a skill cluster than between skill clusters. Using the same methodology, Rinawi and Backes-Gellner (2021), on Swiss data (Social Protection and Labour Market-SESAM for the years 2004-2009), show that skills appear to be transferable across occupations. Nevertheless, a higher occupational specificity appear to be associated with lower job mobility and a longer period of unemployment. Using the Lazear's skill-weights approach on Swiss data from training curricula (vocational education and training (VET) curricula) matched with SESAM from the years 1999 to 2009, Eggenberger, Rinawi and Backes-Gellner (2018) reiterate the results that a higher occupational specificity induces a lower probability of occupational mobility. In terms of methodology, the

Lazear's skill-weights approach allows to study occupational specificity at the level of single skills as well as the resulting bundles of these skills.

Gathmann and Schönberg (2010), using German data (German Qualification and Career Survey, from BIBB and IAB) for four different years: 1979, 1985, 1991/92, and 1998/99, propose the concept of task-specific human capital. The authors underline that employees move to occupations with similar task requirements with a distance of moves that declines with experience. In their methodology, they distinguish task-specific human capital (valuable only in occupations that require skills similar to the current one) from general skills in order to capture the transferability of each task-specific skills across occupations. Gathmann *et al.* (2020), using administrative data on firms and workers in Germany from 1975 to 2008 (German Social Security Records), focus on the effects of mass layoffs. The authors point out small effects on workers or even no effects for those younger than 50 years old who are geographically mobile and escape from the decline in local employment opportunities that are large. Bachmann *et al.* (2019) using the BIBB data as well as administrative data, study the change in job tasks for Germany in the time period 1979-2014. They confirm a strong decline in routine task intensity (RTI) over this time period and show that this has led to higher inflows into and outflows out of unemployment for routine workers.

Alabdulkareem *et al.* (2018), on US job descriptions (from O*NET, 2014/15), calculate the overlap of a set of skills between job pairs using unsupervised clustering techniques and study skill proximity between occupations. They reveal a polarisation in two clusters that cover specific social-cognitive skills and sensory-physical skills of high- and low-wage occupations respectively. This polarisation constrains the career mobility of workers especially of low-skilled workers. Del Rio-Chanona *et al.* (2021), also provide an analysis of occupational mobility using US occupational transitions data, from January 2001 to September 2018. They generate an occupational mobility network and their analysis takes into account occupations impacted by automation shocks and they highlight that in some regions of the occupational mobility network, workers easily find new jobs and others regions where workers get trapped because there are no good alternatives, causing an increase of long-term unemployment. Alabdulkareem *et al.* (2018) and Del Rio-Chanona *et al.* (2021) both map skills complementarity (and produce a skillscape) by proceeding in four main stages (1) calculate the revealed comparative advantage of each skill in an occupation; (2) calculate the minimum of the conditional probabilities of a pair of skills being effectively used by the same occupation; (3) identify skill types using a unsupervised clustering techniques with a community detection algorithm; (4) map the skillscape. Frank *et al.* (2018) exploit US data identifying the employment distribution of occupations across 380 US metropolitan statistical areas (MSAs) and combined statistical areas (CSAs) in 2014 in order to add a geographical mobility feature in the analysis. They show that the potential impact of automation in large cities is lower than in small cities because in large cities many jobs are in managerial and technical occupations less impacted by automation. Börner *et al.* (2018) use millions of academic publications, courses (from the Open Syllabus Project), and job advertisements (from Burning Glass technologies) published between January 2010 and December 2016 to study the misalignment between skills required on the labour market and skills provided by education institutions. They develop a topical basemap covering skills that occur in job, course, and publication data and reveal that the demand for 'soft' social skills (like teamwork, communication, negotiation, and persuasion) increase with greater demand for 'hard' technical skills.

Regarding the change of skill requirements over time, the descriptions by keywords in (news-papers) job advertisements that require problem-oriented thinking have almost doubled in the US. The trend towards these so-called *'analytical skills'* has been fostered in particular by innovations in information and communication technology (ICT) and also takes place within narrowly defined job titles such as real estate agent (Atalay *et al.* 2018; 2020).

According to recent studies relying on online job vacancy data, the skill requirements by companies increase during an economic crisis. This is due to the fact that during a crisis the number of unemployed - including skilled workers - increases. This means that companies have a larger number of qualified workers at their disposal, who are usually the first to benefit from the economic recovery. For example, in the US, an increase in occupational demands has been observed in regions that experienced high unemployment during the 2007/08 financial crisis (Hershbein & Kahn, 2018; Modestino *et al.,* 2020). Nevertheless, during the recovery period (2010 to 2014) skill requirements by companies appears to fell (Modestino *et al.,* 2016).

Moreover, studies suggest that increasing job demands contribute to growing wage. The reason is that especially regions with a high share of firms with increasing job demands show a growing gap in pay (Deming & Kahn, 2018). It should be pointed out that technological change also affects highly skilled workers with jobs that are highly job-specific and regularly subject to major changes. STEM occupations with complex and specific skill requirements are particularly affected, as they have a high frequency of new jobs and turnover of new hires (Deming & Noray, 2020).

In Europe, using Italian online job vacancies (OJV) data from 2016/17, Colombo, Mercorio & Mezzanzanica (2019) shed light on the fact that non-digital hard skills, soft skills (in particular thinking and social interaction) and part of digital skills (advanced ICT skills and skills related to communication and social media) tend to be negatively related to the probability of automation of a given occupation. They also underline the complementarity/substitutability of hard and soft skills in their relationship with job automation. Giabelli, Malandri, Mercorio, Mezzanzanica & Seveso (2020) use online job vacancies collected in 2018 in the United Kingdom with the aim to identify new emerging occupations. 43 were identified and are mostly related to data management or software and app development. Giabelli, Malandri, Mercorio and Mezzanzanica (2020), use online job vacancies collected between 2018 and 2019 for France, Germany, and the United Kingdom. In terms of methodologies, they proceed in four stages: (1) they calculate weighted Jaccard similarity to measure the skills similarity between occupations; (2) they measure the skill complementarity by exploiting the effective use of skills by occupations; (3) they define the Graph Data Model (GraphLMI); (4) they plot skills' proximity ('clique') across occupation and countries. For each country, a clique is composed of skills that are linked by relationships to which a skill complementarity value of 1 is associated. Their aim is to provide the skills of a specific occupation to be acquired by workers who would like to be mobile across countries.

2. Meso level analysis

2.1. Tangible ICT, intangible capital and income inequality[6]

The world is facing a wave of technological change brought about by disruptive technologies, such as AI, machine learning and robotics. It is thought that this range of new technologies will initiate an industrial revolution by fusing the physical, digital and biological worlds and impacting all disciplines, economies and industries Schwab (2017). One can argue that technological change has historically created more jobs than it has destroyed over the longer term (thanks to the process of creative destruction according to Joseph A. Schumpeter and discussed in Aghion *et al.* (2021). However, future developments are difficult to extrapolate from past experiences. The vast amount of uncertainty about the future trajectory of technology and its economic consequences in periods

[6] This text under this heading is taken from Stehrer (2022), 'The impact of capital accumulation by asset types on labour demand and income distribution'. UNTANGLED deliverable 4.1.

of rupture pose a serious problem for policymakers and raise questions about the effects of technical change on employment. In particular, digitalisation and employment have been attracting much attention.

The key concern that remains heavily debated is the influence of such new technologies on the labour market. Job losses due to automatisation range from 47%, found by Frey and Osborne (2017), to less than 10% as reported by the OECD in Arntz *et al.* (2016). The latter study is less alarming, particularly because the time spans over which this might occur have not been specified. The difference to Frey and Osborne (2017) is that, rather than looking at whole employment sectors, they evaluated the potential automatability (defined as the risk of automation being above 70%) of tasks within an occupation. Nedelkoska and Quintini (2018) subsequently expanded the coverage of countries and occupational titles. Their results suggested that about 14% of jobs in OECD countries face the risk of being highly automatable.

A number of papers have focused on the introduction of robots. Sachs and Kotlikoff (2012), Benzell *et al.* (2015) and Sachs *et al.* (2015) have come to the conclusion that the introduction of robots would boost productivity in the short term but decrease wages and consumption in the long term (see also Zeira, 1998). A recent and comprehensive framework was developed in a study by Acemoglu and Restrepo (2017). In this framework, robots can substitute for specific labour tasks, which is likely to reduce employment and wages. Nonetheless, labour may perform new tasks in which it has a comparative advantage over robots. Focusing on US labour markets, Acemoglu and Restrepo (2018b), using data from EU KLEMS and studies on robot use over the period of 1970-2007, found that the adoption of robots has led to large and robust declines in employment and wages. By contrast, Graetz and Michaels (2018) tested the effects of robot use on labour productivity growth, TFP growth, output prices and employment and did not find a significant negative impact on employment. The reason for this is although robots increase labour productivity growth and TFP growth, these productivity gains also decrease output prices and have an offsetting effect. A recent report by the European Bank for Reconstruction and Development (EBRD, 2018) found similar results for emerging economies. Autor and Salomons (2018) estimated the effect of TFP growth on employment via different channels: own-industry effects, upstream-industry effects, downstream-industry effects and final-demand effects. They concluded that TFP has negative direct effects but positive indirect effects on employment; however, other channels are dominant, and the overall effect of technological progress on employment is thus slightly positive. See Autor and Salomons (2017) and Autor (2015) for an overview.

Ghodsi *et al.* (2019) used this framework and quantified the impacts of robots on employment using a wider sample of countries and controlling for TFP growth. Their results indicated no significant impact on employment but suggested a positive and significant effect on real value added growth. [7] This approach, that relies on a labour demand function derived from a CobbDouglas production function, has been heavily criticised (Felipe *et al.*, 2020; Felipe & McCombie, 2019). Some recent papers have confirmed only a very modest impact of robotisation on employment growth in Europe (see Ant´on *et al.*, 2020; Jestl, 2022).

In other literature, not only the impact on the levels of employment but also the structure of employment have been considered. [8] Prettner and Bloom (2020) (Chapter 3) summarised a number of papers. They broadly concluded that automation has a positive impact on labour productivity. However, there are negative employment and wage effects for low-skilled workers (mainly in manufacturing), whereas the effects for high-skilled workers are insignificant or even positive. Overall, this leads to a decline in the labour income share. However, this should be seen in the longer-term context. Since the 1980s, the composition of the labour force and the remuneration of skills in advanced economies have undergone structural changes and a decline in the demand for high school graduates (medium skilled) relative to college graduates (high skilled) in particular, as documented in Goos *et al.* (2019). It has also been documented that the demand for medium-skilled workers has even declined relative to low-skilled workers, which has led to a so-called polarisation of the labour market, mostly documented in the US and the UK but to a lesser extent in the rest of Europe (Goos and Manning, 2007; Goos *et al.*, 2009; Acemoglu & Autor, 2011). Specifically, the diffusion of digital technologies since the 1980s has accelerated this process (Autor *et al.*, 2003). However, not only technological change but also international trade and offshoring may have been the main driving forces behind this pattern, as emphasised in (Goos *et al.*, 2014; Autor *et al.*, 2015; Acemoglu *et al.*, 2016).

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[7] In earlier papers, R&D spillovers have been modelled in a similar way (see Nishioka & Ripoll, 2012). Adarov and Stehrer (2019a) focused on the roles of the accumulation of capital by asset types and foreign direct investments.
[8] For an earlier important contribution, see Berman *et al.* (1998). Other literature have focused more directly on inequality (e.g. Krusell *et al.*, 2000; Dao *et al.,* 2017 or more general aspects (Spitz-Oener, 2006).

With respect to the introduction of ICTs, it can be argued that in the 1980s and 1990s, it was mainly high-skilled workers who possessed computer skills, as education was slow to adapt to the take-up of new technology (Goldin & Katz, 2009). Thus, the demand for high-skilled workers increased in the early adoption phase of digital technologies and raised skill premiums (Krueger, 1993). After the initial stage of the diffusion of digital technologies, they were adopted across all sectors, and education systems began providing students with the demanded digital skills. As a consequence, the increase in wage premiums for high-skilled workers and cognitive skills has slowed down or even stalled since the 2000s, as documented by several studies, notably in the US (Valetta, 2018; Acemoglu & Autor, 2011).

Michaels *et al.* (2014) found that, for 11 OECD countries in 1980-2004, a rise in a sector's ICT intensity, proxied by ICT capital compensation, was associated with a rising wage share for high-skilled workers to the detriment of medium-skilled workers. However, there is also evidence that these patterns may have changed after the global financial crisis. Pichler and Stehrer (2021) corroborated the main findings of Michaels *et al.* (2014) for that period. Focusing on more recent years and based on the EU KLEMS data released in 2019, they found that a larger increase in ICT intensity was generally not associated with an increasing (decreasing) demand for high- (medium-) skilled workers during the period of 2011-2016. In addition, contrary to the findings for the period of 1980-2004 for Western European economies, they argued that a higher ICT intensity was associated with an increase (decrease) in medium- (high-) skilled workers for Eastern European economies in 2011-2016. The driving force behind this pattern appeared to be the service sector. This result should be interpreted carefully, however, owing to the sensitivity to sample selection. The empirical analysis by the MNvR built on the so-called routinisation hypothesis proposed by Autor *et al.* (2003). Their theory suggested that ICT capital can substitute for labour more easily in routine tasks that follow a repetitive pattern and can be carried out by an algorithm or a programmable machine. Capital, by contrast, can complement labour in non-routine cognitive tasks, i.e. tasks that cannot easily be expressed as a set of programmable rules. As routine tasks are mainly concentrated among occupations located in the middle of the wage distribution, while non-routine cognitive tasks are mainly carried out by high-skilled workers, the diffusion of ICT (due to the falling prices of ICT) leads to an increase in demand for workers in well-paid occupations but a lower demand for middle-income jobs, such as clerks and craft workers. While employment in medium-paid occupations has declined and employment in high-paid occupations has increased in almost all developed economies, low-income jobs have seen gains mostly in the US (Autor *et al.*, 2003) and the UK (Goos & Manning, 2007) but to a lesser extent in the EU (Goos *et al.*, 2019).

The described structural shifts in labour demand have primarily been measured as a change in hours worked in specific occupations. For example, Acemoglu and Autor (2011) and Oesch and Menés (2011) ranked occupations based on their income in a base year and measured the changes in employment within these occupations. Based on 1980 US data, Michaels *et al.* (2014) linked the occupations to the skill level of the workforce (proxied by education). The authors found that occupations that were characterised by non-routine cognitive tasks were mostly occupied by high-skilled workers. Medium-skilled workers were more likely to conduct routine manual and routine cognitive tasks. Finally, low-skilled workers were the largest group within the non-routine manual and routine cognitive occupations. The routinisation hypothesis therefore predicts that ICT increases demand for high-skilled workers but reduces demand for medium-skilled workers, and it gives no clear prediction for low-skilled workers. More recent studies have shown that the wage premium for college graduates has been growing at a slower rate or even stalled around the turn of the millennium in the US (Valetta, 2018; Acemoglu & Autor, 2011). Similarly, Castex and Dechter (2014) found that the return to non-cognitive skills has increased since the 1990s. Beaudry *et al.* (2016) called this trend the 'reversal in the demand for skill'. Edin *et al.* (2017) summarised several explanations put forward to explain this trend. Deming (2017) claimed that the demand for skill is shifting and highlighted that wage growth has been stronger in occupations that require social skills. Beaudry *et al.* (2016) argued that the early investment stage saw high and growing demand for cognitive tasks to facilitate the adoption of digital technologies. As digital skills and the use of ICT became ubiquitous, the technology reached maturity and eventually reduced the premium for digital skills. Hershbein and Kahn (2017) corroborated this argument and showed that occupations that were traditionally characterised by routine tasks experienced upskilling, particularly during the global financial crisis. This implies that workers with cognitive skills are increasingly drawn to less well-paid occupations. A complementary argument by Brynjolfsson and McAfee (2014) suggested that the progress in computing technology has allowed capital to compete more effectively with non-routine cognitive tasks, thereby lowering demand for high-skilled workers.

2.2. Productivity, intangible asset dispersion and wage inequality

An increasing attention has been devoted in the last years to the firm-level drivers of wage inequality (Card *et al.*, 2018). In imperfect labour markets, firms can adopt a variety of wage-setting practices shaping a firm-level wage premium that could reflect differences in productivity, rent-sharing, an efficiency wage premium, or strategic wage posting behaviour. When wage premia are asymmetric between groups of workers, they generate heterogeneity of wage gaps between firms (Aghion *et al.,* 2018; Cirillo *et al.*, 2017). These firm-specific premia may also explain a relevant part of the wage inequality between regular and vulnerable workers. Notably, by including women in the group of vulnerable workers and focusing on gender wage gap, the OECD (2021b) pointed out that this gap amounted to 22% for similarly-qualified men and women. About three quarters of this gap is based on differences in pay observed within firms and it is not negligeable the portion of the gap due to work of equal value, where statistical discrimination and bargaining power take the lion share.

On the other hand, Card *et al.* (2016) and Blau and Kahn (2017) identified two factors affecting the wage of women relative to that of men: (i) the between firm sorting channel conjecture explains that the gender pay gap is due to the differentials between higher and lower paying workplaces in which men and women are respectively hired; (ii) the possibility that equally productive men and women have different relative bargaining power.

A complementary strand of literature deals with the effect of incentive pay schemes (IPSs) on gender wage gap. On the whole, IPSs solve potential moral hazard problems within companies by setting higher wages that elicit the right effort from the workers. If these incentives are only implemented for those workers whose tasks are difficult to monitor, the within-firm wage inequality arises (Lazear & Rosen, 1981; Lazear, 1986; Murphy, 1999; Cirillo *et al.*, 2017). Interestingly, some authors are currently concentrating on the influence that IPSs may exert on gender wage gap (Manning & Saidi, 2010; Zwysen 2021; Arabadjieva & Zwysen, 2022). According to this literature, either women more likely work in positions where IPS is not implemented or they less likely receive these bonuses for similar jobs (Zwysen 2021; Arabadjieva & Zwysen, 2022). This supports the view of IPS widening the gender pay gap. However, Manning and Saidi (2010) found modest evidence for differential sorting into IPS by gender and very small, even insignificant, effects of IPS on hourly wage differentials between men and women. One explanation they give, among others, is that it may be more difficult to discriminate against women under IPSs, where pay and productivity end up more aligned.

Indeed, the impact of IPS on gender wage gap could be the result of other factors that shape the context in which the latter takes place. For example, some authors pointed out that investments in intangibles tend to increase gender inequalities, by increasing returns in job positions where men tend to be over represented (e.g. Meyersson Milgrom *et al.*, 2001; Korkeamäki & Kyyrä, 2006). Especially when intangibles correspond to investments in databases and software (or ICT), women are not only under-represented in industries where the digitalisation is more intensive (Segovia-Peréz *et al.*, 2019) but jobs in these contexts offer more flexible and unpredictable working hour arrangements that notably hinder the access of women with household responsibilities (Goldin, 2014; OECD, 2017; 2019d).

2.3. Labour market adjustment to shocks

The pursuit of economic and social convergence is one of the EU's founding principles. Decades of research concludes that the free movement of goods, services, and labour has increased living standards in the EU and has contributed to socio-economic convergence, although the process is far from completed and large differences in terms of wellbeing and welfare exist across the EU (Crespo Cuaresma *et al.*, 2008). The EU regional support mechanisms have contributed to supporting poorer regions and to reducing inequalities between the regions (Becker *et al.*, 2010; Cappelen *et al.*, 2003).

Adverse labour market shocks may, however, halt or slow down convergence in the EU. Technological transformation, globalisation and the transition to a low-carbon society will create skill-biased shocks in labour demand, which will differ by region. Some regions will experience increasing demand for labour, while other regions will suffer from a lack of demand. An extensive literature has shown that local joblessness is very persistent: regions often need several decades to recover from severe negative demand shocks (Overman & Puga, 2002; OECD, 2005).

One important channel through which labour demand shocks can be absorbed is labour mobility between regions or countries. This effect is estimated to be rather substantial with some studies indicating labour mobility to absorb up to about a quarter of an asymmetric economic shock within a year in Europe (Arpaia, Kiss, Palvolgyi & Turrini, 2016; Jauer, Liebig, Martin & Puhani, 2019). Beyer and Smets (2015) even report labour mobility to account for about 50% of the long-run adjustment to region-specific labour demand shocks in both Europe and in the United States. Other recent studies, however, argue that previous work exaggerates the migratory response (Amior & Manning, 2018; Greenaway-McGrevy & Hood, 2014). In addition, Dao, Furceri and Loungani (2014), and Beyer and Smets (2015) find that the contribution of migration in the US has decreased. In Europe, nonetheless, the contribution seems to have increased in recent years (Beyer & Smets, 2015).

The (magnitude of the) migratory response depends on multiple factors. First, migration is more likely within currency areas. This was, among others, illustrated by Arpaia *et al.* (2016) who estimate the movements in response to shocks to have almost doubled since the inception of the euro. Second, foreign-born individuals are found to have a higher propensity to migrate than natives (Basso, D'Amuri & Peri, 2019). Additionally, in Europe, the migratory response was found to largely stem from migration of recent EU accession country citizens and third-country nationals (Jauer *et al.*, 2019).

Often the migratory response is investigated through a vector autoregression (VAR) approach (based on the pivotal work of Blanchard & Katz, 1992) (see e.g. Arpaia *et al.*, 2016; Beyer & Smets, 2015). This method offers an indirect measure of population change, including migration but also ageing and mortality, as all employment changes unexplained by the participation and the employment rate are implied to originate from a change in population. In addition, supply side factors, such as retirement decisions, can also impact local employment. Therefore, recent studies consider an instrumental variable (IV) approach, which better isolates demand shocks and allows to control for contemporaneous shocks.

The latter approach was adopted by Amior and Manning (2018), who studied the persistence of unemployment across US commuting zones. The researchers further extended on the approach by introducing an error-correction mechanism. Using this approach Amior and Manning find a strong migratory response to a decline in demand, but as further demand contractions are likely to follow, the population never catches up. Within the euro area and also using the IV approach, Basso *et al.* (2019) find a similar migratory response of foreign-born individuals as compared to the US. EA natives, however, are less mobile than their foreign-born peers.

2.4. Technological transformation and European regions[9]

Radical and complex transformations are taking place in contemporary economies and society because of the exponential evolution and global adoption of the new technologies, such as artificial intelligence, smart automation, and the internet of things. Optimism about the growth and productivity potential offered by 4.0 technologies diffusion is widespread even if the risks of possible social threats cannot be ignored and are increasingly highlighted (Frey & Osborne, 2017; Schwab, 2017; Brynjolfsson & McAfee, 2014; McAfee & Brynjolfsson, 2017; Rullani & Rullani, 2018).

The role of the new technologies in the transformation of industrial production processes, known as Industry 4.0, has received great attention in the literature also from a spatial perspective and has highlighted the important consequences of the increasing automation and digitalisation of the manufacturing environment (Acemoglu & Restrepo, 2020; Büchi *et al.*, 2020). Digitalisation, in fact, enriches value chains and the exchange of inputs with business partners, supplier and customers (Lasi *et al.*, 2014). The integration of physical objects in the information network represents a deep revolution in the traditional industry and pushes towards a paradigm shift in production processes and business models, setting a new level of development and management for organisations (Paiva Santos *et al.*, 2018; Ciffolilli & Muscio, 2018).

In particular, the relevance of digital technologies in the renewal and transformation of manufacturing activities has been soon acknowledged in the literature on servitisation. Scholars in this field have richly documented the shift in manufacturing business models towards the provision of bundles of product and (digital) services turning into a symbiotic recoupling between manufacturing and service activities (Rabetino *et al.*, 2021; Gebauer *et al.*, 2021; Kohtamäki *et al.*, 2021a). Importantly, digitalisation enables expanding the range of hybrid/integrated offerings (products and services) toward digital offerings. Since customers increasingly show preferences for receiving only the value inherently offered by the product use and consuming it as a service, this strategy looks more and more attractive (Cusumano, Kahl & Suarez, 2015; Tukker, 2004).

Conversely, far less is known about what we define in this work as the *digital service economy*, an economy encompassing a sprawling range of businesses, enabled by digital platforms, redesigning the boundaries of products towards services. The idea of digital service economy differs from and

[9] This text under this heading is taken from here is taken from Capello, Lenzi and Panzera (2022) (UNTANGLED deliverable 4.6).

enriches the concepts of service economy proposed by Buera and Kaboski (2012) as well as alternative labels introduced in the literature and in the policy debate to describe the application of digital technologies in products and services creation and provision, such as the digital economy (OECD, 2020; EC, 2021).[10] In our understanding, in fact, the digital service economy does not simply refer to the expansion of service sectors over manufacturing in terms of both value added and employment, as the service economy would imply (Buera & Kaboski, 2012). Nor does it simply relate to the deployment of digital technologies in the provision of products and services through on-line channels, as implicit in the notion of digital economy. The digital service economy, instead, refers to the idea that the full-scale digitalisation trend characterising modern economies and society is redesigning the boundaries between product and services, with the latter not only complementing and/or enriching the former (as proposed in the case of servitisation and its literature) but also, and increasingly, *substituting* them. The dematerialisation of the product (e.g. a CD) into its own content (e.g. music) allows the last one to be sold online in the form of a digital service (e.g. a subscription to Spotify), destroying the market of the original product in favour of the service.

This encompassing view on the complex relationship between products and services admittedly finds its origins in the vast literature on servitisation and the reflections on product-service (innovation) systems (see for reviews Rabetino *et al.*, 2021; Baines *et al.*, 2017 on servitisation; Baines *et al.,* 2007 on product-service systems). Over time, however, additional digital market transactions have come to the fore that forge on-line markets through the operation of digital platforms, including phenomena like the sharing economy (e.g. BlaBlaCar), the on-line service economy (e.g. Uber) up to the digital content economy (e.g. Spotify, Netflix). All these forms go under the notion of digital service economy. In short, the digital service economy can be defined as an economy characterised by the redesign of the boundaries between manufacturing and services in favour of the latter, enabled by the increasing dematerialisation or unbundling of resources and products (e.g. a car) from the service they may provide (e.g. a ride). Consequently, the digital service economy expands the opportunities and choices of consumers to get a product and/or a service. For example, if a person needs a car, 'he can buy a second-hand car using a website (e.g. Ebay), he can rent a car on a car-rental company website (e.g. Herzt or Car2Go), he can hire on-demand an individual to

[10] https://www.oecd.org/sti/ieconomy/oecd-digital-economy-outlook-2020-bb167041-en.htm, last visited 01/02/2022; https://digital-strategy.ec.europa.eu/en/policies/desi, last visited 01/02/2022.

drive on his place using a site (e.g. Uber), he can rent a car from a private individual (e.g. Relayrides)' (Frenken *et al.*, 2015, p. 5).

An in-depth analysis of the digital service economy is still missing. It is, however, particularly crucial at least for two reasons. First, typifying the different modes through which the digital service economy can take place (and, thus, redesign the boundaries between products and services) enables identifying the actors involved in market exchanges and, thus, how economic value is created and distributed among them. This effort is warranted as digitalisation is expanding the ways of doing business, opening to new formal and informal rules in the ways markets operate. The awareness of the plurality of actors and sources of value creation involved in the different types of digital service economy is crucial in order to understand, anticipate and, if needed, mitigate the socio-economic consequences the digital service economy may generate. In fact, its expansion opens opportunities for business activities and on-call contingent work, but it is also feared for the potential instability and low quality of jobs being created, and for the possibly unequal income distribution generated. The measurement of such positive and negative effects and their final balance in different economies requires a clear identification of the different value creation and distribution models, and their respective actors, involved in the digital service economy.

Second, the territorial dimension of the digital service economy has been somewhat neglected in the literature. In fact, existing evidence focuses on single business case studies, specific technologies, specific areas, missing a Europe-wide territorial comparative perspective. This is particularly unfortunate given the important debate on territorial servitisation and knowledge-intensive business services (KIBS) flourished in the last years (Capello & Lenzi, 2021a; De Propris & Bailey, 2020; Barzotto *et al.*, 2019; Vaillant *et al.*, 2021; Sisti & Goena, 2020; Gomes *et al.*, 2019; Sforzi & Boix, 2019; Vendrell-Herrero & Bustinza, 2020). Yet, there is urgent need of deeper knowledge and understanding of which value creation model prevails in a local economy so to be able to anticipate its socio-economic impacts. As long as digital platforms enable the large-scale, ubiquitous diffusion of technologies, the digital service economy can generate widespread benefits for users and (independent) service providers located not only in advanced regions but also in more remote and peripheral ones.

The digital service economy: its value creation models

Digitalisation is revolutionising market transaction mechanisms, and thus value creation models, and is increasingly pushing businesses to sell services, products or contents on on-line markets, frequently managed by platforms. Digital platforms replace bilateral with trilateral relationships, involving a producer (a worker, a content producer, a service producer), a requester, and the platform (Koutsimpogiorgos *et al.*, 2020). A digital platform can therefore be defined as a 'matchmaker' between producers who offer a production capacity and recipients interested to use, buy, or enjoy it (Kornberger *et al.*, 2017).

3. Macro level analysis

This chapter summarises the extant state-of-the-art of the work package 5: Micro-level analysis.

The three mega trends studied in UNTANGLED (digitalisation, globalisation, demographic changes) influence the nature of work, the occupational skill bundles required, and thereby the match quality on the labour market (Acemoglu & Autor, 2011). Moreover, unfilled job vacancies provide opportunities for job candidates to move, while a lot of skills are portable across occupations (Gathmann & Schönberg, 2010; Rinawi & Backes-Gellner, 2021). Yet, on average, only 3% of European workers are occupationally mobile (Bachmann *et al.*, 2019) but with large differences across EU countries, for instance in UK 12% of workers are mobile (Carrillo-Tudela *et al.*, 2016). Skill mismatch is an important issue that has detrimental effects on job quality, worker effort, and firm performance (Martin, 2020). Improving match quality and facilitating occupational mobility appear as key policies to prepare the workforce for the future (Gathmann *et al.*, 2020).

3.1. Firm-level productivity, profitability, innovations, and managerial and organisational capabilities

One of the most important challenges for the EU's future is how to ensure paths of inclusive growth, and innovation is a key ingredient in this process (EU Commission, 2019). The literature has long established that innovation comprises both technological and non-technological aspects (Fagerberg *et al.*, 2005). As concerns technological innovation, recent academic research as well as policy interest (including at the EU level), has revolved around the opportunities and challenges associated with the generation and adoption of AI, and more in general fourth industrial revolution technologies (FIRTs) and their impact on productivity, employment and wage inequalities

(Acemoglu & Restrepo, 2020; Autor, 2015; Frey & Osborne, 2017; Arntz *et al.*, 2016). This fourth industrial revolution, also known as industry 4.0 in manufacturing, bares new digital paradigms including a vast array of technologies. These 'game-changing' or disrupting technologies can find widespread application across every manufacturing industry due to their 'versatility and complementarity' (Eurofound, 2018). The disruptiveness of these technologies resides not just in their power to affect products and their production processes, but also in the implications they have for businesses and the working condition of their employees. Despite the bulk of attention given to technologies of the FIRT, empirical evidence concerning these phenomena is still limited, along with a suitable measure of adoption allowing a serious investigation of the effects of such technologies on a large scale across countries and sectors in the long run.

Fourth industrial revolution technologies (FIRTs)

An increasing body of evidence has sought to study theoretically and empirical the expansive effect of FIRTs on productivity growth. According to the most optimistic view, AI and robotisation could significantly increase the rate of GDP growth through factor substitution and productivity spillovers (Aghion *et al.*, 2018, Nordhaus, 2020). Some pioneering studies simulate that aggregate rate of rate of *labour* productivity or GDP growth may accelerate by between 1 and 4% as a result of AI diffusion (Bughin *et al.*, 2018). More plausibly, Graetz and Michaels (2018) estimate that, in OECD industries, *labour* productivity has increased by 0.4-0.8 percentage as a result of robotisation (see Kromann *et al.,* 2019 for comparable findings).

Venturini (2022) documents that the development of *FIRTs* has produced significant aggregate productivity spillovers, explaining around 8% of the observed variation in productivity among OECD countries. As for any General Purpose Technologies GPT, the productivity impact of *FIRT* would show up with some delay, following a J-shaped curve (Brynjolfsson *et al.,* 2020). The magnitude of these effects is in the same order of the impact found by Edquist *et al.* (2019) for the Internet-of-Things (IoT).

At the firm level, automation is found to act a significant driver of firm performance, contributing to expanding company output by 0.02 and 0.07% (Kromann & Sørensen, 2020). Alderucci *et al.* (2020) for the US and Damioli *et al.* (2021) for the EU illustrate that companies innovating in AI are much more productivity than their counterparts. In a similar vein, Babina *et al.* (2020) document that companies investing in AI expand faster than non-AI investing firms.

Managerial and organisational capabilities (MOCs)

With reference to non-technological innovations, managerial and organisational capabilities (MOCs) have emerged as a key potential source of economic performance and competitive advantages of firms (Bloom & Van Reenen, 2007; 2010; Dosi & Nelson, 2010; Helfat & Martin, 2015; Teece, 2016).

Bloom and Van Reenen (2007; 2010) provided with useful and simplified theoretical framework to analyse managerial capabilities; the latter can be easily operationalised and connected with the empirical work. Within this theoretical framework the *management quality* is seen as a set of practices that explains part of profitability, boosts total factor productivity and other residual parts of measured performances not explained by new *hard technological innovation* (new machinery or new products). Management activities are classified as *operation*, *monitoring*, *target* and *incentive practices* and evaluated by means of a *double blind survey* that proved to be robust to potential biases incorporated in the responses of firms and preconceptions of interviewers. However, according to Bloom and Van Reenen (2011), also these managerial best practices can be seen as a technology; this technology is unevenly spread across rational and profit maximising firms because information and incentives problems, regulatory constraints and externalities raise a number of adoption costs. These authors also discuss behavioural explanations of managerial capabilities, even though the latter remain marginal in their research. In this case, the heterogeneity in the diffusion of best management practices is interpreted in a theoretical context of non-optimising firms that potentially could suffer from managerial overconfidence and procrastination problems. In line with this research field, other authors investigated the effectiveness of incentive practices and pay for performance schemes across different institutional and technological contexts, such as unionised vs non-unionised firms (Damiani *et al.*, 2016), family vs non-family firms (Damiani *et al.*, 2018; Pompei *et al.*, 2019), companies operating in high-tech sectors vs business knowledge intensive service sectors (Cardinaleschi *et al.*, 2019).

Another line of research bases MOCs on the evolutionary theory of innovative firms (Dosi *et al.*, 2000; Dosi and Nelson, 2010; Teece, 2010); by following this view firms are seen as boundedly rational and non-optimising agents endowed with stocks of idiosyncratic and firm-specific assets (both tangible and intangible). These assets/resources are difficult to trade and hardly can be transferred from one firm to another because they are built within the firm, co-evolve and co-specialise in specific contexts and organisations. According to Teece (2016), entrepreneurial management requires different, complex and specific knowledge to develop a creative vision, to discover and create opportunities, to sense customer needs and anticipate marketplace responses. Very often these abilities are not uniformly distributed among individuals. Thus, managers show different levels of these abilities. In addition, a single manager is not expected to be able to perform all the activities mentioned above. That is why it is a management team that very often tackle highly complex issues and bears responsibility for the future of the organisation. A good management team is not only expected to develop skills (human capital) within the firm, but it should also allow the diffusion of trust and respect of others (social capital), in order to improve the overall organisational capabilities. Therefore, the uneven distribution of assets, resources and capabilities among firms explains the large heterogeneity observed among the firms' performances.

It is worth noting that Teece (2016) explicitly considers the best managerial practices introduced by Bloom and Van Reenen (2007; 2011) as ordinary capabilities; it means that they are sufficient '… in the performance of a well delineated task' (Teece, 2016, p. 210) and can be measured against the requirement of specific targets, such as labour productivity or time to completion. By contrast, only strong dynamic capabilities guarantee long-term performances and competitive advantages to firms. This is because the dynamic capabilities encompass a more general ability to recognise threats and opportunities, to identify business environment changes and to prevent organisational rigidities. In more detail, Teece (2007) grouped the dynamic capabilities according the following activities: (i) identification, development and assessment of technological opportunities in relationship to customer needs (sensing); (ii) mobilisation of resources to address needs and opportunities (seizing); (iii) continued renewal of resources and competences (transforming). Thus, firms' dynamic capabilities only partially reside with CEO and top managers, the other pillar being values and culture of the whole firm's organisation and the collective ability to implement new business models and other changes. According to Nonaka (2000), this collective ability, involves quality control circles that may be implemented by quality management systems (such as ISO 9001). Actually, results concerning the impact of quality management systems, standards and certification on innovation and productivity are still rather inconclusive. On the one hand, it is clear that the standardisation supporting quality management systems provides an important and obvious locus for learning processes, this is because it stimulates the development of a common pool of codified knowledge, that in turn enables and constrains innovation. Despite an increasing empirical literature suggests systematic links between the codified knowledge contained in standards and productivity growth at the level of whole economies, the precise mechanisms involved at the industry- and firm-level are still far from being well understood (King *et al.*, 2017). On the other hand, studies focusing at the firm level does not find results clear-cut. For example, by analysing a sample of Irish firms, Bourke and Roper (2017) explore complementarities between *soft* (*quality circles*) and *hard* (quality certification) quality improvement methods and their influence on *learning-by-using* and product innovation. They find positive and significant effects of quality certification, such as ISO 9001, on product innovation and *learning-by-using*, only when *quality circles* (i.e., small groups of workers who meet regularly on a voluntary basis to discuss problems) are adopted prior to that certification. Terziovski and Guerrero (2014) concentrate on a sample of Australian firms and find that ISO 9001 affects positively only process innovation while it has no significant impact on product innovation. There is instead very sparse evidence about studying potential complementarities between innovation activities and quality certification on productivity of firms. This is quite surprising because quality certification is a specific form of organisational innovation (non-technological innovation) that might be complementary to technological innovations. More in detail, quality certification systems such as those defined by ISO 9001, rely, among others, on the important principle of 'continual improvement and factual approach to decision making' (Kartha, 2004) that strictly resemble to the concept of dynamic capabilities.

Differently from the ordinary capabilities and the best managerial practices, the dynamic capabilities are very hard to measure (Dosi *et al.*, 2018). Drawing on the dynamic capability framework, Adner and Helfat (2003) and Helfat and Martin (2015) attempted to better operationalise dynamic capabilities by introducing the concept of dynamic managerial capabilities, in which only the managerial impact, and not the impact of the whole firm's organisation, on the strategic change is isolated. Three main dimensions shape the dynamic managerial capabilities according to the Helfat and Martin's view (2015): (i) managerial cognition, that is mental models, beliefs and emotions influencing managers in anticipating market changes, understanding the implications of different choices, and ultimately taking action; (ii) managerial social capital, it consists of building informal and formal work relations inside and outside the company, in order to obtain information and easily access to resources, such as financing and skilled personnel, needed for investments to seize opportunities; (iii) managerial human capital, i.e., education, experience and skills. In their review of literature, Helfat and Martin (2015) have found about 50 quantitative empirical studies with evidence concerning the impact of dynamic managerial capabilities on the strategic change efforts. The bulk of them only concentrate on the education and experience of managers and are based on very restricted sample of companies. Much fewer are studies that also consider the managerial social capital, such as the number of direct ties or involvement in business networks of managers (trade associations, chambers of commerce, see for example Bosma *et al.*, 2004; Davidson & Honig, 2003), and the managerial cognition, for example emotions and affective-based actions that lead managers in their strategic choices (Zott & Huy, 2019). Eventually, at the best of our knowledge there is no empirical work that explicitly attempted to operationalise the more general Teece's concept of dynamic capabilities of firms.

3.2. Robot adoption, globalisation and labour market transitions

The rapid increase of robot technology during the last two decades has ignited fears, especially among policy-makers and the general public, of a considerable job loss due to the substitution of workers by automation technologies. This increase is mainly driven by two factors: technological progress and the accompanying decreasing price of robot technology. Advances in technology expand the range of tasks that can be performed by robots and allow their adoption in a greater variety of applications. Through the decreasing price, robots become relatively more attractive as an input to production. This factor is even more important in countries with higher labour costs and those which are more affected by demographic change (Acemoglu & Restrepo, 2018).

According to theory, the ex-ante effect of robots on labour markets and employment is ambiguous and could be either positive or negative (Acemoglu & Restrepo, 2019). The concerns regarding robot adoption are best described by the displacement effect. Thus, robots will take over tasks previously performed by workers if they are more cost efficient per unit of output produced. This effect may, however, be counterbalanced by a productivity effect that increases demand for labour. Evidence from the tasks literature predicts that technology will displace workers mainly in routine tasks that follow a well-defined set of rules and acts as a complement to workers working in non-routine tasks that require complex, problem solving and interpersonal skills (Autor *et al.*, 2003). While there is evidence from industry data in a cross-country setting showing that robot adoption leads to an increase of GDP, labour productivity and wages in industrialised countries (Graetz & Michaels, 2018), studies for specific countries show a more nuanced picture. The heterogenous effects across countries indicate that country specific factors and industry structure play an important role.

In a study for 17 industrialised countries for the time period 1993 to 2007, Graetz and Michaels (2018) show that robots increased labour productivity growth, did not reduce total employment, but reduced the low-skilled employment share. Klenert *et al.* (2020) use industry-level data from the EU-LFS for a number of European countries for the time period 1995 to 2015. They even find that robot use is linked to an increase in aggregate employment, and that employment of low-skilled workers did not fall because of robots. Evidence for a large number of developed and emerging economies shows that the initial development level of a country matters. While robot adoption has contributed to the decline in employment level in routine manual task-intensive jobs in developed countries, it had no significant effect on emerging countries' labour markets (de Vries *et al.*, 2020).

Another reason for cross-country differences in the labour-market effects of robots are institutions. For Germany, Dauth *et al.* (2021) also provide evidence that the effect of robots was stronger in regions with weaker institutions. This is in line with a cross-country study for European countries showing that institutions such as unions can help to mitigate the negative effect of labour market shocks (Bachmann & Felder, 2020).

For the US, Acemoglu & Restrepo (2020), use repeated cross sections from the Census and American Community Survey in order to analyse the effects of robot exposure on local labour markets from 1993 to 2007. They find large negative effects of robots on wages and employment across commuting zones. This stands in contrast to evidence from Germany that shows that the decline in manufacturing employment was offset by an increase in employment in the service sector. Linking firm data to individual panel data, they show that young workers are the ones mostly affected since they face reduced job creation in the manufacturing sector. Instead, these young workers increasingly sort into the service sector (Dauth *et al.*, 2021).

Evidence at the firm level for specific countries can provide more information on the firms adopting robots and automation technology. Studies for France and Spain show that robot adoption leads to expansion and that it increases labour demand (Acemoglu *et al.* 2020; Koch *et al.* 2019). Using firm-level data for France, Acemoglu *et al.* (2020) find that robots increase productivity and overall employment despite decreasing the overall labour share in a firm. However, there is within-firm reallocation from production to non-production workers. Evidence for Spain indicates that this effect is partly driven by positive selection since more productive firms are also more likely to invest in robots (Koch *et al.,* 2019). However, they confirm a positive effect of robot adoption on employment and productivity while they find negative employment effects for non-adopting firms. Results for Denmark also show that the overall positive effects mask heterogenous effects across workers. Adopters increase their demand for IT workers, but production workers are laid off or have to accept lower wage growth (Humlum, 2019).

Changes in labour markets flows in response to a technology shock directly affect the employment and unemployment level. Studying these changes in job separation and job finding can provide interesting information on underlying mechanisms and worker welfare. Evidence for Spain shows that the negative effect of robots on non-adopters is significantly driven by a job higher separation rate (Koch *et al.,* 2019). Instead, Domini *et al.* (2019) find for Italy that employment growth stems from lower separation rates in firms investing in robots.

While the effects of robots on labour-market outcomes is thus an actively-researched field, open questions remain in at least two fields. First, the mechanisms underlying the effects on employment and unemployment stocks have up to now not been explored to a great extent, particularly not in a cross-country context. Second, reasons for cross-country differences, such as labour-market institutions or labour costs, have hardly been explored at the worker level. UNTANGLED therefore aims at making a contribution in these fields.

3.3. Gender, skills, tasks and employment outcomes

The aim of this task is to quantify gender skill gaps in the EU countries, distinguishing between cognitive and non-cognitive (interpersonal or soft skills), and assess how changes in the demand for tasks and skills affect gender gaps in employment outcomes in the EU.

The use of Information and Communication Technologies (ICT) and robots has been changing the world of work in the last few decades. Computers and other digital technologies have changed the structure of jobs tasks performed by humans. They have reduced the role of routine tasks - both manual and cognitive - and increased the role of non-routine cognitive tasks - both analytical and interpersonal (Acemoglu & Autor 2011). These changes in task content occurred both within and across occupations (Autor, Levy & Murnane, 2003; Spitz-Oener, 2006). These development have led to job and wage polarisation in developed countries (Goos, Manning & Salomons, 2014). The hollowing out of the middle-paid jobs has created winners and losers of technological progress and globalisation. The gender dimension of these changes has been important but relatively under-studied. On one hand, routine-replacing technologies increase returns to social skills which women tend to have a comparative advantage in (Deming, 2017) so they benefit more from ICT adoption than men (Jerbashian, 2019). On the other hand, women lag behind men in skills complementary to new technologies: women are less likely than men to study in Science, Technology, Engineering, and Mathematics (STEM) college programmes (Delaney & Devereux, 2019) and exhibit lower numeracy skills (Rebollo-Sanz & De la Rica, 2020). Nevertheless, the adoption of robots in European countries has narrowed the within-occupation and within-sector gender pay gap (Aksoy, Özcan & Philipp, 2021).

The emergence of data that allow measuring worker-level skills and jobs tasks has provided new insights into gender gaps in labour markets. Lewandowski *et al.* (2022) constructed worker-level measures of skills and job tasks for a wide set of high-, middle-, and low-income countries, and found that women perform more routine-intensive tasks than men with comparable jobs and skill levels. These gender differences are especially pronounced among workers in high-skilled occupations (ISCO 1-3) and workers in low-skilled occupations (ISCO 7-9), and smaller among workers in middle-skilled occupations (ISCO 4-5) (Lewandowski *et al.* 2022).

Several studies analysed the association between gender differences in skills, tasks and labour market outcomes. The contribution of numeracy skills in explaining the gender gaps in labour market participation and hourly wages is limited (Rebollo-Sanz & De la Rica, 2020; De la Rica, Gortazar & Lewandowski, 2020) which means that only a small share of existing gender gaps in labour market outcomes can be attributed to lower skill levels among women. Also, after accounting for worker-level job tasks a significant gender wage gap in hourly wages remains significant (De la Rica, Gortazar & Lewandowski, 2020) which suggests that women are paid less for performing similar tasks than those performed by men also if they possess comparable levels of skills. These studies used pooled cross-country data. Tverdostup and Paas (2022) showed that the contributions of different components of human capital to explaining the gender wage gap varies a lot between countries. The work experience related to a current position is the only component of human capital consistently decreasing gender wage disparities. The contribution of numeracy to explaining the gender wage gap varies from 22% in Ireland to a negative effect in Lithuania (-9.7%).

3.4. Firm human capital investment, wage inequality and employment

Training is seen as an investment in firm-specific human capital and is undertaken to raise workers' productivity. The impact of these investments can be distinguished along two dimensions. The first looks at productivity and other measures of firm-level performance; the second looks at the wage and employment opportunities of trained employees. In the latest three decades, increasing attention has been paid to understanding the effect of training investment. These intangible assets are found to raise firm productivity and output whilst the impact on wages seems smaller, yielding thus a positive net premium at the firm (Bartel 1995, Konings & Vanormelingen, 2015). This Recent evidence also shows that training enlarges the knowledge base and hence can raise the firm innovation capacity (McGuirk *et al.,* 2015). The effect of training on employees' conditions largely depends on the ability of the workers under training. Since returns to training may differ according to the schooling level or other employee characteristics, this type of investment may widen wage differentials or employment conditions among group of workers (Marcotte, 2000).

Measurement implementation

During the past six months the activity related to the development of Task 5.4 has been focused on the screening and analysis of the existing data sources for generating firm level estimates of firm specific human capital for the European economies. Our estimation strategy follows the approach adopted by INTAN Invest to generate measures of training investments at the industry level on the basis of the information provided by the Continuing Vocational Training Survey, Eurostat (CVTS)[11] (Corrado *et al.*, 2016). INTAN Invest adopts an expenditure approach resorting to cost data and their methodology satisfy the following criteria:

- **Exhaustiveness**. A comprehensive measure of training investment incorporates the estimate of two main components: own-account and purchased training.
- **Consistency with national accounts**. National accounts data are a highly valuable data source for economic analysis mainly because they are consistent over time and across countries at any level of industry detail. NA consistency is obtained using NA data as the main data source, modifying them only to extend the SNA/ESA asset boundary to include new intangible assets, among which training; and taking into account the necessary adjustments of additional variables (value added, gross operating surplus) to guarantee NA internal consistency of when the asset boundary is extended.

[11] The last wave of CVT (2015) microdata covers the following countries: Belgium, Bulgaria, Czechia, Denmark Germany, Estonia, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden, United Kingdom and Norway. CVTS covers enterprises with 10 or more persons employed in the business economy (mainly). The total net sample sise for the 24 countries is about 111,000 enterprises.

- **Reproducibility and international comparability**. To guarantee reproducibility and international comparability, INTAN Invest estimates are based on official data sources homogeneous across countries.

As for the firm level estimates of training investment we will use the information gathered from firm's balance sheets on the costs of employees and training expenditures gathered from BvD ORBIS Europe and AIDA merged with the data from the CVTS and we will check their consistency with industry level measures from INTAN Invest.

3.5. The drivers of job quality in Europe

Regarding the state-of-the-art related to job quality, most of the existing studies do not relate to all components of job quality identified by United Nations Economic Commission for Europe (2015). These components are: (1) Safety and ethics of employment, (2) Income and benefits from employment, (3) Working time and work-life, (4) Security of employment and social protection, (5) Social dialogue, (6) Skills development and training, (7) Employment-related relationships and work motivation.

For instance, using the European Working Conditions Survey (EWCS), Green and Mostafa (2012) focus on income, fair treatment, employment-related relationships and work motivation (skills and discretion, good social environment, good physical environment, work intensity) and working time. Regarding trends of these four components between 1995 and 2010 in the EU-15, they show a relative stability in skills and discretion, good physical environment and work intensity and a slight increase in working time quality. Holman *et al.* (2015) on the same data and period, reveal that training and working time have increased as well as physical demands and work intensity, whereas job discretion and cognitive demand have decreased. They do not find clear patterns of convergence among EU-15 countries for job quality as measured by all its dimensions but do find convergence for specific dimensions such as the amount of training and working time. Fernandez Macias *et al.* (2014) provide, also using EWCS data, the evolution of job quality from 2000 to 2010 in the EU-15 focusing on a composite indicator covering five dimensions: earnings, employment-related relationships and work motivation, faire treatment in employment, safety at work, and work-life balance. They do not observe a major decline during the period, even during the economic crisis but detect some convergence between EU countries with a small increase in job quality in peripheral European countries.

There is little existing evidence directly relating job quality changes induced by digital transformations. A notable exception is Dauth *et al.* (2021) who study the impact of robot usage in Germany between 1994 and 2014, on employment and job quality, which is measured according to four dimensions: median wage, share of workers with a college degree, and the intensity of abstract tasks. They find that robot adoption leads to displacement in manufacturing, mainly among new entrants to the labour market, but this is offset by new jobs in services. However, automation is linked to more stable jobs for incumbents as they take on new tasks in their original plants, with these new jobs being of higher quality than the old jobs.

Other studies look at job satisfaction. Holman *et al.* (2015) find descriptive evidence that less computerised occupations have seen a faster decline in job satisfaction and an increase in workload relative people working in more computerised occupations. Schwabe and Castellacci (2020) find that, over the period from 2016 to 2019, automation in industrial firms in Norway led to 40% of workers fearing they may be replaced by machines in the future. This negatively affects job satisfaction, mainly among lower skilled workers carrying out routine tasks.

Some other scholars focus essentially on outcomes like wages, hours of work and job security (e.g. Autor & Dorn, 2013; Bessen *et al.,* 2019; De La Rica *et al.,* 2020). Regarding wages, De La Rica *et al.* (2020) on 19 developed OECD countries (PIAAC data from 2011-12 and 2014-15) show that macro level differences in ICT capital per worker and computer use are related to routine task intensity of jobs performed by workers. They also underline that non-routine cognitive tasks (or abstract tasks) are positively related to wage premium whereas routine tasks manual tasks are negatively related to wage premium. Ross (2017) finds the same qualitative results for the US over the period 2004 to 2013 which underlines that an increase in routine task content induces a decrease in wages while an increase in abstract content lead to an increase in wages. Edin *et al.* (2019), on Sweden between 1986 and 2013, show that workers who sort into a declining occupation upon entering the labour market suffer from a decline in earnings. Workers in the bottom tercile of their declining occupations' earnings distributions suffered the largest losses. Fossen and Sorgner (2019), on US data from 2011-2018, reveal that computerisation risk is associated with lower wages, whereas artificial intelligence complements workers' skills and increases wages. Webb (2020) in contrast finds that recent Artificial Intelligence innovations are directed at taking over jobs of high skilled individuals and predict a decrease in (one measure of) wage inequality. Lane and Saint-Martin (2021) conclude in a review of the impact of AI on employment and wages that there is no support for the notion that AI will reduce wage and employment in occupations exposed to AI. Graetz and Michaels (2018) examine the impact of robot adoption within industries across 17 countries from 1993 to 2007. They find that greater robot led to increased labour productivity and higher wages, without significantly reducing total employment.

Regarding other components of job quality, Bessen *et al.* (2019), on data from the Netherlands (2000 to 2016), reveal that for workers employed in firms that adopt robots face significantly lower job security. Using German data, from 2004 to 2014, Abeliansky and Beulmann (2021) find that increased use of industrial robots has negative effects on the mental health of workers, which is driven by fears relating to income and working hours. Coupe (2019), on US data from 2015, examines whether certain job characteristics, that are thought to be automation proof, are linked to greater job security. The findings indicate that workers with jobs requiring personal interaction, which may be harder to substitute with robots or automation, are less concerned with job loss. However, automation does not appear to be a major driver of insecurity, as the majority of workers concerned about automation are also concerned about job security for other reasons. Schmidpeter and Winter-Ebmer (2018) use Austrian data from 2012 to 2014 to investigate the impact of automation risk, based on routine task intensity, on the probability of re-employment of unemployed individuals and post-employment outcomes. Automation risk is found to be associated with a lower probability of re-employment, and lower future wages and employment duration.

Menon *et al.* (2020), on European data (EWCS) from 1995 to 2015, show that changes in computer use are related to other facets of job quality like work discretion and intensity. With another perspective taking into account the intergenerational mobility on data from the British Cohort Study (1975, 1980, 1986, 1991, 1996, 2000, 2004 and 2008), Dolan and Lordan (2020) show that (relative) upward intergenerational mobility impacts positively life satisfaction and (relative and absolute) upward intergenerational mobility is negatively related to mental health, whereas a downward mobility (relative and absolute) has detrimental effects on subjective well-being.

The literature review provided by Castellacci and Tveito (2018) emphasises that digital tools used at the workplace were shown to enhance communication and access to information through new tools and networks (e.g. intranet, internal and external platforms at the workplace). They can positively affect knowledge sharing which contribute to improving workers' skills, and human relations within teams and firms. In the end, they can increase firms' capacity to innovate as well as their profitability (Bertschek *et al.*, 2013) which, in turn, offers more opportunities for these firms to raise wages and promote their employees (who will be happier). By distinguishing Information Technologies (IT that facilitate access to information and knowledge such as workflow like Slack or Freedcamp) and Communication Technologies (CT that reduce internal communication costs like groupware, e.g. Dropbox), Bloom, Garicano, Sadun and Van Reenen (2014); Martin (2017, 2020b) identify that IT decentralise decision making and motivate employees while CT centralise decision making and demotivate employees.

The COVID-19 pandemic influenced also the job quality of workers. For instance, Cotofan *et al.* (2021) regarding various well-being indicators such as negative affect (depression, anxiety, worry, and lack of interest in daily activities), or happiness at work, highlight heterogeneity between countries and variation all along 2020 in parallel to changes in sanitary restrictions. Teleworkers have also immediate benefits such as greater autonomy and avoiding the commute (and the expenses associated with it) but may suffer for social isolation. Ahrendt *et al.* (2020) underlines that EU-27 teleworkers are less likely to feel they are doing a useful job, they more often reported high job demands and they more often reported feeling isolated. Teleworkers reported working in their free time, especially when there are children in the household. Indeed, respondents with children under 17 who worked only from home during the COVID-19 crisis reported a greater degree of work-life imbalance. Sostero, Milasi, Hurley, Fernandez-Macías and Bisello (2020), on EU data (EWCS), show that the telework induced by the lockdown was strongly biases in favour of high-paid white-collar employment. Nevertheless, the enforced closures have likely resulted in many new teleworkers amongst low and mid-level clerical and administrative workers who previously had limited access to teleworking.

Gihleb *et al.* (2020) also look at health outcomes associated with the adoption of robots in the US form 2005 to 2011. They find that a one standard deviation increase in robot exposure leads to a 16% reduction in work-related injuries. However, there is a positive link between robot exposure and drug or alcohol related deaths, which may be linked to adverse employment effects associated with robot adoption. Gunadi and Ryu (2021) also examine the effect of robotic technology on health in the US from 2006 to 2017. They find that greater use of industrial robots is positively related to the health of low-skilled workers. Specifically, a 10% increase in robots per 1,000 workers is associated with a 10% reduction in the share of low-skilled workers reporting poor health. The authors indicate that task reallocation may be responsible, as physical tasks are shifted to the industrial robots.

A novel study that links automation to work-life balance and relationships is Anelli *et al.* (2019). They find that regions in the US with a greater intensity of robots experienced a decrease in new marriages and an increase in divorces during the period from 2005 to 2016. The hypothesis put forward to explain these findings is that greater robot use leads to increased uncertainty and a reduced willingness for long-term commitments.

Skills development is an important component of job quality. McGuinness *et al.* (2021), on European data (Cedefop European Skills and Jobs Survey of 2015, 2018), examine how exposure to technological change relates to skills development and training. They find workers exposed to technological change were more likely to experience skills enhancement and receive on-the-job training. They also find a positive link between exposure to technological change and task variety. Nevertheless, they also show that workers affected by automation experience greater job insecurity.

Bartel *et al.* (2007) study a specific industry, US valve manufacturing, from 1999 to 2003. They find that the adoption of IT-enhanced equipment leads to an in increase in technical and problem-solving skills among machine operators, with new human resource practices introduced to support these new skills. Spitz-Oener (2006), on German data from 1979 to 1999, examines how skill requirements in German jobs have changed over time and finds that computerisation has led to an increase in job complexity. Black and Spitz-Oener (2010), on West Germany from 1979 to 1999, find that technological change has led to a reduction in routine tasks performed by women, which in turn helps to explain the decline in the gender wage gap over time.

4. Scenario building

This section documents the state-of-the-art underlying the work in UNTANGLED WP6, 'Scenarios for Europe and its territory'. The main goal of WP6 is the development of scenarios for Europe and its territory, based on different assumptions on the intertwined driving forces highlighted in WPs 3-5, i.e. technological transformation, globalisation and demography.

One component in tasks 1-3 is a Delphi survey. The Delphi technique is used to involve UNTANGLED's stakeholder community in the scenario building. The technique involves a series of sequential questionnaires or 'rounds', interspersed by controlled feedback, to attain the most reliable consensus of opinion of a group of experts (Powell, 2003; Niederberger & Renn, 2019). Stakeholders are first asked to validate the assumptions (derived from the results of WPs 3-5), and then to validate the scenarios, to ensure these are in line with their experiences and expectations, but also to suggest alternative angles on policy implications.

4.1. Building scenarios

The need for anticipatory and far-seeing economic policies has always induced economists to seek reliable methodologies with which to produce insights on what the future will look like. Among existing alternative methodological exercises, the distinction between forecasts and foresights is useful, and it helps guide the approach used here.

In general, the aim of a forecast is to obtain precise values of specific economic variables in the future, on the basis of extrapolations of a system of past socio-economic relations. Exactly because they extrapolate from past tendencies, forecasts yield the best results in a short-term perspective. The aim of a forecasting exercise is, in general, to achieve a quantitative value in a certain year, paying little attention to the intermediate path, or to the feedback and adjustment processes by which the end value is determined (Armstrong, 1985; Hawkins, 2001; Hendry & Clements, 2001; Loomis & Cox, 2000).

Foresight is a radically different exercise. It is mostly qualitative in nature, and its aim is to provide an image of the future based on radical breaks, on structural effects which destroy past tendencies. A new technological paradigm, new socio-cultural models, new political regimes are all examples of structural breaks in the elements regulating an economic system which give rise to completely new and radically different images of the future. A foresight is a possible, probable and even desirable image of the future under the assumption that these events, or perhaps only one of them, will occur. Contrary to forecasts, foresights do not address the dynamic processes that will produce the final outcome; rather, they explore the general consistency of the final image by analysing all the adjustment processes that are likely to happen. In general, a foresight is built on an image of what the future will look (explorative projections), but also of what the future should look (desirable projections). Foresight provides insights into the future based on a structural and radical break with the past, and assuming in general a long-term perspective (usually decades) (CEC, 2004; Miles & Keenan, 2000; UNIDO, 2004).

The logic of the methodology used in this work is neither that of a pure forecast nor that of a pure foresight. Our approach can be defined as a quantitative foresight in that it is the result of three major steps. The first involves scenario building whereby an image of the future is constructed on the assumption that a discontinuity will emerge in the main elements or driving forces that influence and regulate the system. The second step is to insert these changes into a model of structural relationships which in traditional manner links conditional (explanatory) variables and the dependent variables. The qualitative assumptions of the first-step procedure are translated into quantitative ones linking the expected driving forces to specific values of the model's independent causal variables. The third step involves a simulation procedure leading to a 'conditional' forecast of the dependent variables (Capello *et al.*, 2008). The intention is not to provide precise estimates of future GDP levels, but rather to highlight the main tendencies, major adjustments to change, relative behavioural paths that will be at work, given some conditional assumptions about the influence of the main driving forces.

4.2. Scenarios on regional GDP and employment growth

The scenario methodology described under task 6.1 has largely been applied on the basis of a model of structural relationships called MASST (Macroeconometric, sectoral, social and territorial regional growth model) (Capello *et al.*, 2017). The MASST model was conceived with the aim to fill a gap in the existing literature on forecasting regional growth models. In fact, the landscape of available toolboxes was made up of two classes of models. On the one hand, some forecasting regional growth models were based on a distributional logic whereby national growth rates simulated or forecasted in macro models were reassigned to regions constituting the countries modelled using regional GDP and employment shares as weights. In more sophisticated versions, this redistribution could take place by means of input-output linkages. On the other hand, other forecasting regional growth models focused on the purely regional component, relatively ignoring the important consequences that macro shocks could exert on regional growth rates.

MASST was conceived as a way to overcome this dichotomy and interpret regional growth as both a top-down and bottom-up process. This implied, from a theoretical perspective, a marriage between two opposing views on regional growth; a bottom-up/top-down regional growth view on the one hand, and a demand-side/supply-side view on the other hand. In other words, it had the aim to create a new model whereby national and regional growth would have to feed back to one another, thus truly striking a balance between the two theoretical approaches.

Its interpretative power has been tested through its application to a baseline scenario forecasting GDP growth for 2030 that was run at the end of 2013 (Camagni *et al.*, 2016). In this simulation, the

MASST model forecasted the emerging trend of divergence in GDP growth among European regions, in a period in which macroeconomic forces were forcing superior (but regionally differentiated) constraints to all regions (national fiscal crises, austerity measures, exchange rate devaluations and internal devaluations). Secondly, comparing two scenarios driven respectively by mega-cities and by medium and medium-large cities the latter scenario proved to be at the same time the most expanding and the most cohesive (Camagni *et al.*, 2015). In the same vein, MASST has been applied to several scenario building exercises, from the costs of an enduring crisis (Capello *et al.*, 2015; 2016), to the costs of a dismembering process in the EU (Capello *et al.*, 2017; 2018), providing sound messages and raising awareness of the risks embedded in political and economic turmoil.

4.3. Scenarios on skills composition of the labour force

Peri and Sparber (2009) is the first paper that documents occupational upgrading of natives after an inflow of immigrants. The source of this mechanism comes from the fact that natives and immigrants specialise in different types of jobs, the former in cognitive, the latter in manual tasks. D'Amuri and Peri (2014) find that immigration to the European Union allows incumbents to switch to increasingly complex tasks, and stimulates hiring without increasing separations. Even though they implement the national skill cell approach of Borjas (2003) and Ottaviano and Peri (2012), report reduced-form, non-structural estimates, and analyse labour markets in partial equilibria, these are the first findings of natives' skill upgrading in the European context. Similar outcomes have been found by Cattaneo *et al.* (2015) using a very different research design. With an access to longitudinal panel data on labour market outcomes (The European Community Household Panel), the authors are able to control for individual heterogeneity, which solves the conceptual problems of education-experience approach. They find three labour market effects for native incumbents: (i) transition to higher ranked occupations, (ii) increasing wages, and (iii) no change in unemployment probability. Foged and Peri (2016) report similar findings by investigating longitudinal data on the universe of Danish employees. Low-skilled immigration of refugees substituted similar Danish workers, and incentivised them to move upwards in the occupational ladder. Workers experience slightly positive wage effects, and decide to move internally. Peri and Sparber (2011) study the US labour market and find that foreign-born workers with graduate degrees specialise in occupations demanding quantitative and analytical skills, while natives specialise in occupations requiring interactive and communication skills. Lin (2019) takes a local labour market approach, and documents how foreign college workers in STEM occupations affect the task specialisation of native college workers in U.S. cities. He finds no evidence of occupational displacement but documents positive wage effects of foreign STEM flows on college natives, particularly for those in high-social occupations. Bound *et al.* (2015) and (2017) simulate the distributive labour market consequences of hiring computer scientists through an H-1B visa program in the US, and report significant wage and employment effects within the IT industry.

There is also a growing literature on the effect of automation, technological change, and job polarisation on allocation of immigrant workers across occupations and regions. A number of studies focused on high-skill and STEM workers. Siu and Jaimovich (2017) find that immigration of highly educated workers reduces wage inequality when non-routine-biased technological change advances. Cadena and Kovak (2016) document stronger geographical mobility of Mexican immigrants in the US induced by labour market shocks. Consequently, the presence of immigrants attenuates the labour market effects of exogenous shocks for native workers. Basso *et al.* (2018) show that immigrants mitigate occupational displacement effects of computerisation by increasing demand for goods and services produced by routine jobs. They construct a measure of local computer adoption at work for the period 1980–2010, and show its strong relation to immigration of both high and low skilled workers, and of high-skill natives. Moreover, they document that foreign workers are largely responsible for the growth of manual-intensive service employment, thus contributing to the low-end employment polarisation. With a help of calibrated partial equilibrium model, they also postulate that migration mitigates job polarisation, reverses de-routinisation of native employment, induces natives' skill upgrading, and raises wages of natives active in routine-intensive occupations.

One important feature of labour markets that is missing from the analysed skill-task models is the multidimensional heterogeneity of workers, labour markets and occupations. As motivated by Autor and Handel (2013), and Firpo *et al.* (2011), the self-selection model in the vein of Roy (1951) is better suited for the analysis of labour market displacement. These models assume that individuals possess continuously distributed, multidimensional vectors of skills. Different jobs reward different skills in a non-uniform way, which motivates workers to self-select across occupations/sectors. Recent applications of this rich theory, for example, Costinot and Vogel (2015), Burstein *et al.* (2019; 2020), make use of a self-selection model with a Frechet distribution of types. While this improves the tractability of the model, it also implies that labour market shocks have no effect on the variance and skewness of log wages in the population of native workers. The post-selection distributions of wages are equalised across labour markets. Thus, while such models have much to say about who gains and who loses from migration, they are silent on the link between migration, technology and changes in overall inequality.

Gola (2021) allows for workers' endogenous choice between discrete sectors driven by comparative advantage, and within sector matching between skills and jobs determined by absolute advantage in performing complex tasks by individuals that are more skilled, as in Costrell and Loury (2004); Dupuy (2015); Sattinger (1975; 1979); and Teulings (1995; 2005). Thus, Gola (2021) is the first paper that solves the endogenous problem of two-layer assignment in one unified framework, by joining the literatures of Roy (1951) self-selection and Sattinger (1975) matching. However, his analysis is restricted to partial labour market equilibrium. Burzyński and Gola, (2020), who quantify the economic impact of Mexican migration to the US, propose an extension of Gola (2021) into a two-sector, general equilibrium model. Their theoretical model allows to disentangle short-run labour market effects, expressed as changes in wages offered by firms due to labour supply chocks, long-run labour market effects induced by a readjustment of equilibrium demand for firms (free entry or exit of firms), and the market size effects which appears as a consumption externality. The calibration of the model fits continuous distributions of wages in sending and receiving countries, the number of Mexican migrants to the US, shares of unemployed workers, and the structures of country-specific GDPs. Their main findings–the impact of migration in the sending and receiving economies along wage distributions–relate to the supply and distribution of skills, the implied selection of migrants, and the complementarity between skills and jobs. The normative part of the paper includes simulating the consequences of changing visa costs, US trade tariffs, supply of US-relevant skills in Mexico, and dealing with illegal migration from Mexico. A richer, yet more tractable theoretical approach constitutes the modelling core of this research proposal.

4.4. Policy simulations

This sub-section describes the state-of-the-art related to existing policy recommendations and policy simulation.

In order to improve skills of the workforce and economic performance of companies, two main type of policies can be adopted by policymakers: (1) the ones that modify the supply of labour (e.g.

changes in education); (2) the ones that modify the demand for labour by firms (e.g. subsidies for companies to invest in automation).

Most of existing policy recommendations focus on the first type of policies. At the EU level, The European commission defined in 2020 the 'Digital Education Action Plan for the period 2021-2017' (European Commission, 2020) to improve the skills of the European workforce by investing in digital education and training. They target two strategic priorities: (1) fostering the development of a high-performing digital education ecosystem and (2) enhancing digital skills and competences for the digital transformation. The European Commission also invests in digital skills through the 'New Skills Agenda for Europe' and 'Digital Skills and Jobs Coalition initiative'. They underline although the role of social partners to support individuals that work in the gig economy (i.e. on crowd-sourcing or crowd-working platform). At a larger scale, OECD launched in 2012, the 'Skills Strategy' to support members and partners to enhance their skills systems by supporting projects in ten OECD Member countries (Austria, Belgium [Flanders], Italy, Korea, Mexico, the Netherlands, Norway, Portugal, Slovenia and Spain) and in one non-Member (Peru). This strategy updated in 2019 (OECD, 2019c) with a focus on lifelong learning (OECD, 2021a) and on policy priorities to improve skills impacted by megatrends, including technological change, globalisation and demographic changes (population ageing, migration). Griffin *et al.* (2012) present studies of various policy frameworks and reforms in education assessment and teaching with the aim to identify effective solutions to address the barriers associated with the improvement of skills and foster large-scale adoption of assessment reforms. De Groen *et al.* (2017) provide also some policy recommendations regarding upskilling programs and highlight the importance of adapting the education and training systems. They cite programs in Japan and South Korea and show the relevance of training programs in digital literacy and science, technology, engineering and mathematics (STEM). At the European country level, specific policies are developed, for instance, in Norway, in order to ensure that individuals and firms developed skills that provide a competitive business environment and an inclusive labour market (Norwegian Ministry of Education and Research, 2017). Cedefop (2012) investigates the effect of training at the workplace using data collected on employees aged between 30 and 55 in Germany, Hungary, the Netherlands and Finland in 2011. The report shows that workers in non-supportive organisations are more affected by skills obsolescence than those from enterprises that encourage learning, and that skills obsolescence is greater in non skill-intensive jobs. Pouliakas (2018), using the ESJS data from the Cedefop collected in EU-28 in 2014, quantifies the effects of firm investment in training. He shows that the commitment of firms to the development of the skills of their staff reduces the original estimate of 14% of workers facing a very high risk of automation to 8.3% (for firms that fully reimburse the cost of training) or to 7.6% (for firms that partly reimburse training expenditure). For unemployed people, it seems useful to enlarge their occupational search. Grounded on the results of Papageorgiou (2014) and Groes *et al.* (2013) that highlight a time-consuming and costly process of workers continuous learning about finding appropriate occupations, Belot *et al.* (2019) provide and test with a 'field-in-the-lab' approach with an online tailored advice tool for unemployed in UK. They show that it allows unemployed to enlarge the set of occupations they consider and increase the number of job interviews. Nevertheless, Ernst *et al.* (2018) underline that skills policy are necessary but not sufficient. Moreover, all of these previous studies do not cover to Covid-19 pandemic that affects the labour market. The simulation exercise provided by Burzyński (2020) reveal that induced demand shocks affect the employment, the requested skills, the real demand, the sector-specific demand, the probability of bankruptcy, and the fixed cost of all sectors. As an illustration, the winners are in the transportation and storage sector while the losers are in the sale sector.

Moving on to the second type of policies targeting the demand for labour by firms and especially subsidies to support upward transition, evidence remains scarce. For instance, Giorcelli (2019) examines the effects of providing management training and granted technologically advanced machines to a subpopulation of Italian companies in the 1950's. She reveals that the performance of companies who sent managers and/or engineers to US to be trained increased for at least fifteen years after the program; performance of companies that received new machines increased, but flattened out over time and that management and new machines were complementary.

In addition, new forms of regulating the digital economy are called for that prevent further rises in market concentration, ensure proper data protection and privacy and help share the benefits of productivity growth through a combination of profit sharing, (digital) capital taxation and a reduction in working time. Goolsbee (2018) proposes indeed various policies on pricing and privacy such as restrictions on consumer privacy and the ways that companies can use customer information, and competition policy such as anti-trust policy to limit the winner-take-all market structure or 'platform' competition.

Regarding scenarios and simulation exercises, once again, few studies exist. For instance, Méda (2016) proposes three independent scenarios for the future of work: (1) dismantling labour law;

(2) technological revolution and (3) ecological conversion. She shows that the latter is the best to foster employment in Europe while supporting economic efficacy and social justice. Schroder (2020) proposes some simulation exercises on economic policies aimed at increasing trade protections, and labour market policies aimed at the demand for skilled trades, personal service, and machine operators. He simulates a theoretical model on UK over the period 2009 to 2018 and shows that his recommended policies reduce income and wealth inequalities (of employed white British males, aged between 25 and 55 years).

References

Abeliansky, A., & Prettner, K. (2017). Automation & demographic change. *Hohenheim Discussion Papers in Business, Economics, & Social Sciences, University of Hoheneim, Germany 05-2017.*

Abeliansky, A.L., & Beulmann, M. (2021). Are they coming for us? Industrial robots & the mental health of workers. *Center for European Governance & Economic Development Research, Discussion Paper No. 379.*

Acemoglu D., & Restrepo P. (2020), Robots & Jobs: Evidence from US Labor Markets, *Journal of Political Economy, 126* (6).

Acemoglu, D., & Autor, D.H. (2011). Skills, tasks & technologies: Implications for employment & earnings. In D. Card & O. C. Ashenfelter (Eds.), *Handbook of Labor Economics, 4*, Part B, 1043-1171. https://doi.org/10.1016/S0169-7218(11)02410-5.

Acemoglu, A., Autor, D., Dorn, D., Hanson,G., & Price, B. (2016). Import competition and the great us employment sag of the 2000s, *Journal of Labor Economics, 34*(1), 141–198.

Acemoglu, D., & Restrepo, P. (2017). Secular stagnation? The effect of aging on economic growth in the age of automation, *American Economic Review, 107*(5), 174–179.

Acemoglu, D., & Restrepo, P. (2018a). Demographics & automation. *NBER Working Paper 24421*.

Acemoglu, D., & Restrepo, P. (2018b). The race between machine & man: Implications of technology for growth, factor shares & employment, *American Economic Review, 108*(6), 1488–1542.

Acemoglu, D., & Restrepo, P. (2019). Automation & new tasks: How technology displaces & reinstates labor, *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3.

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

Acemoglu, D., & Restrepo, P. (2020). Robots & Jobs: Evidence from US Labor Markets, *Journal of Political Economy, 128*(6), 2188–2244. https://doi.org/10.1086/705716.

Acemoglu, D., & Restrepo, P. (2020). Robots & jobs: Evidence from US labor markets, *Journal of Political Economy, 128*(6), 2188-2244.

Acemoglu, D., & Restrepo, P. (2021). Demographics & automation, *The Review of Economic Studies,* (Forthcoming). https://doi.org/10.1093/restud/rdab031.

Acemoglu, D., Lelarge, C., & Restrepo, P. (2020). Competing with Robots: Firm-Level Evidence from France. *AEA Papers & Proceedings, 110*, 383–388.

Acemoglu, D., Lelarge, C., & Restrepo, P. (2020). Competing with robots: Firm-level evidence from France. *AEA Papers & Proceedings, 110*, 383–388. https://doi.org/10.1257/pandp.20201003.

Acemoglu, D., & Restrepo, P. (2018). Demographics & Automation. *NBER Working Paper No. 24421.*

Acemoglu, D., & Restrepo, P. (2019) Automation & New Tasks: How Technology Displaces & Reinstates Labor, *Journal of Economic Perspectives, 33*(2), Spring 2019.

Acemoglu, D., & Autor, D.H. (2011). Skills, Tasks & Technologies: Implications for Employment & Earnings In *Handbook of Labor Economics*, edited by David Card & Orley Ashenfelter, 4:1043–1171. Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5.

Adarov, A., & Stehrer, R. (2019a). Implications of foreign direct investment, capital formation and its structure for global value chains. *wiiw Working Paper 170*.

Adarov, A. & Stehrer, R. (2019b). Tangible and intangible assets in the growth performance of the EU, Japan and the US. *wiiw Research Report 442*(44244).

Adarov, A., & Stehrer, R. (2020). New productivity drivers: Revisiting the role of digital capital, fdi and integration at aggregate and sectoral levels. *wiiw Working Paper 178*.

Adner, R., & Helfat, C.E. (2003). Corporate effects & dynamic managerial capabilities, *Strategic management journal*, *24*(10), 1011-1025.

Aghion, P., Akcigit, U., Hyytinen, A., & Toivanen, O. (2018). On the returns to invention within firms: Evidence from Finland. *AEA Papers and Proceedings* (Vol. 108, pp. 208-12).

Aghion, P., Antonin, C., & Bunel, S. (2021). *The Power of Creative Destruction: Economic Upheaval and the Wealth of Nations.* Harvard University Press.

Aghion P., Jones B.F., & Jones C.I. (2018). Artificial Intelligence & economic growth. In: A.K. Agrawal, J. Gans, A. Goldfarb (Eds.), *The Economics of Artificial Intelligence: An Agenda*. University of Chicago Press. URL http://www.nber.org/chapters/c14015.

Antón, J.-I., Klenert, D., Fernández-Macías, E.F., Urzi Brancati, M.C., & Alaveras, G. (2020). The labour market impact of robotisation in Europe. *JRC Working Papers Series on Labour, Education and Technology 2020/06*.

Ahrendt, D., Cabrita, J., Clerici, E., Hurley, J., Leončikas, T., Mascherini, M., … Sándor, E. (2020). *Living, working & COVID-19.* Eurofound COVID-19 Series. Luxembourg: Publications Office of the European Union.

Aksoy, G.C., Özcan, B., & Philipp, J. (2021). Robots & the Gender Pay Gap in Europe, *European Economic Review 134* (March): 103693. https://doi.org/10.1016/j.euroecorev.2021.103693.

Alabdulkareem, A., Frank, M.R., Sun, L., AlShebli, B., Hidalgo, C., & Rahwan, I. (2018). Unpacking the polarization of workplace skills, *Science Advances, 4(*7), 1–10. https://doi.org/10.1126/sciadv.aao6030.

Aldaz Odriozola, L., & Eguía Peña, B. (2016). Immigration & Occupational Mobility of Native Workers in Spain. A Gender Perspective, *Journal of International Migration & Integration, 17*(4). https://doi.org/10.1007/s12134-015-0459-4.

Alderucci, D., Branstetter, L., Hovy, E., Runge, A., & Zolas, N. (2020). Quantifying the impact of AI on productivity & labor demand: Evidence from U.S. Census microdata. *Unpublished manuscript*, Carnegie Mellon University.

Amior, M., & Manning, A. (2018). The persistence of local joblessness. *American Economic Review, 108*(7), 1942-1970.

Anelli, M., Giuntella, O., & Stella, L. (2019). Robots, labor markets, & family behavior. *IZA Discussion Paper No 12820.*

Arabadjieva, K., & Zwysen, W. (2022). Gender inequality in performance-related pay: a gap in the EU equal pay agenda. *ETUI Research Paper-Policy Brief*.

Armstrong, S.J. (1985). *Long Range Forecasting. From Crystal Ball to Computer.* New York: A Wiley Interscience Publ., John Wiley & Sons.

Arntz, M.,Gregory, T., & Zierahn, U. (2016). The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis, *OECD Social, Employment and Migration Working Papers*, No. 189. Paris: OECD Publishing, https://doi.org/10.1787/5jlz9h56dvq7-en.

Arpaia, A., Kiss, A., Palvolgyi, B., & Turrini, A. (2016). Labour mobility and labour market adjustment in the EU, *IZA Journal of Migration, 5(*1), 1-21.

Atalay, E., Phongthiengtham, P., Sotelo, S., & Tannenbaum, D. (2018). New technologies & the labor market, *Journal of Monetary Economics, 97,* 48–67. https://doi.org/10.1016/j.jmoneco.2018.05.008.

Atalay, E., Phongthiengtham, P., Sotelo, S., & Tannenbaum, D. (2020). The evolution of work in the United States. *American Economic Journal: Applied Economics, 12*(2), 1–34. https://doi.org/10.1257/app.20190070

Autor, D. (2015). Why are there still so many jobs? the history and future of workplace automation, *Journal of Economic Perspectives 29(3)*, 3–30.

Autor, D.H. (2019). Work of the past, work of the future. *American Economic Association Papers & Proceedings, 109*(5), 1-32. https://doi.org/10.1257/pandp.20191110

Autor, D.H., & Dorn, D. (2013). The growth of low-skill service jobs & the polarization of the US labor market, *American Economic Review, 103(*5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553

Autor, D.H., & Handel, M.J. (2013). Putting tasks to the test: Human capital, job tasks, & wages, *Journal of Labor Economics, 31*(S1), S59–S96. https://doi.org/10.1086/669332.

Autor, D.H., Dorn, D., & Hanson, G.H. (2013). The China syndrome: Local labor market effects of import competition in the United States, *American Economic Review, 103*(6), 2121–2168. https://doi.org/10.1257/aer.103.6.2121.

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*(4), 1279–1333. https://doi.org/10.1162/003355303322552801.

Autor, D.H. (2015). Why are there still so many jobs? The history & future of workplace automation, *Journal of economic perspectives, 29*(3), 3-30.

Autor, D.H., Dorn, D., & Hanson, G.H. (2015). Untangling Trade & Technology: Evidence from Local Labour Markets, *Econ J, 125,* 621-646.

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*(4), 1279-1333.

Autor, D., & Salomons, A. (2017). Robocalypse now – does productivity growth threaten employment? In European Central Bank (Ed.), *Investment and Growth in Advanced Economies*, 45-118.

Autor, D., & Salomons, A. (2018). Is automation labor-displacing? Productivity growth, employment, and the labor share, *Brookings Papers on Economic Activity 49(1)*, 1–63.

Babina, T., Fedyk, A., He, A.X., & Hodson, J. (2020). *Artificial intelligence, firm growth, & industry concentration.* Unpublished manuscript. Columbia University.

Bachmann, R., & Felder, R. (2021). Labour market transitions, shocks & institutions in turbulent times: a cross-country analysis. *Empirica, 48*(2), 329–352. https://doi.org/10.1007/s10663-019-09469-y.

Bachmann, R., Bechara, P., & Vonnahme, C. (2019). Occupational mobility in Europe : extent, determinants & consequences. *IZA Discussion Paper No 12679.*

Bachmann, R., Cim, M., & Green, C. (2019). Long-run patterns of labour market polarization: Evidence from German micro data, *British Journal of Industrial Relations, 57*(2), 350–376. https://doi.org/10.1111/bjir.12419.

Bachmann, R., Gonschor, M., Lewandowski, P., & Madon, K. (2022). The effects of robots on labour market transitions in the EU. *Ruhr Economic Paper 933 and IBS Working Papers 01/2022*. UNTANGLED Deliverable 5.2.

Baines, T.S., Lightfoot, H.W., Evans, S., Neely, A., Greenough, R., Peppard, J., Alcock, J.R. (2007). State-of-the-art in product-service systems, Proceedings of the Institution of Mechanical Engineers, Part B: *Journal of Engineering Manufacture, 221* (10), 1543-1552.

Baines, T., Bigdeli, A.Z., Bustinza, O.F., Guang, V., Baldwin, J., Ridgway, K. (2017). Servitization: revisiting the state-of-the-art & research priorities, *International Journal of Operations & Production Management, 37*(2), 256–278.

Bartel, A.P. (1995). Training, Wage Growth, & Job Performance: Evidence from a Company Database, *Journal of Labor Economics 13*(3), 401–425.

Bartel, A., Ichniowski, C., & Shaw, K. (2007). How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement & worker skills, *The Quarterly Journal of Economics, 122*(4), 1721–1758. https://doi.org/10.1162/qjec.2007.122.4.1721.

Barzotto, M., Corradini, C., Fai F., Labory, S. & Tomlinson, P.R. (Eds.) (2019). *Revitalising Lagging Regions: Smart Specialisation & Industry 4.0.* Oxford: Routledge.

Basso, G., D'Amuri, F., & Peri, G. (2019). Immigrants, labor market dynamics and adjustment to shocks in the Euro Area, *IMF Economic Review, 67*(3), 528-572.

Basso, G., Peri, G., & Rahman, A. (2020). Computerization & immigration: Theory & evidence from the United States. *Canadian Journal of Economics, 53*(4), 1457–1494. https://doi.org/https://doi.org/10.1111/caje.12472.

Becker, S.O., Egger, P.H., & Von Ehrlich, M. (2010). Going NUTS: The effect of EU Structural Funds on regional performance, *Journal of Public Economics, 94*(9-10), 578-590.

Beaudry, P., Green, D.A., & Sand, B.M. (2016). The great reversal in the demand for skill and cognitive tasks, *Journal of Labor Economics 34(1)*, 199–247.

Behaghel, L., Caroli, E. & Roger, M. (2014). Age-biased Technical & Organizational Change, Training & Employment Prospects of Older Workers, *Economica, 81*, 368-389.

Belk, R. (2007). Why not Share Rather than Own? *The Annals of the American Academy of Political & Social Science, 611*(1), 126-140.

Belot, M., Kircher, P., & Muller, P. (2019). Providing advice to jobseekers at low cost: An experimental study on online advice, *The Review of Economic Studies, 86*(4), 1411-1447. https://doi.org/10.1093/restud/rdy059.

Benkler, Y. (2002). Intellectual property & the organization of information production, *International Review of Law & Economics, 22*(1), 81-107.

Ben-Porath, Y. (1967). The production of human capital & the life cycle of earnings, *Journal of Political Economy 75*(4), 352–365.

Benzell, S., Kotlikoff, L., LaGarda, G., & Sachs, J.D. (2015). Robots are us: Some economics of human replacement. *NBER Working Paper 20941*.

Berman, E., Bound, J., & Machin, S. (1998). Implications of skill-biased technological change: International evidence, *The Quarterly Journal of Economics, 113(4)*, 1245–1279.

Bertschek, I., Cerquera, D., & Klein, G.J. (2013). More bits-more bucks? Measuring the impact of broadband internet on firm performance, *Information Economics & Policy, 25*(3), 190-203. https://doi.org/10.1016/j.infoecopol.2012.11.002.

Bessen, J.E., Goos, M., Salomons, A.M., & Van Den Berge, W. (2019). Automatic reaction - What happens to workers at firms that automate? *SSRN Electronic Journal* No 3328877 (Vol. 19).

Beyer, R.C., & Smets, F. (2015). Labour market adjustments and migration in Europe and the United States: how different? *Economic Policy, 30*(84), 643-682.

Black, S. E., & Spitz-Oener, A. (2010). Explaining women's success: Technological change & the skill content of women's work, *Review of Economics & Statistics, 92*(1), 187-194. https://doi.org/10.1162/rest.2009.11761.

Blanchard, O.J., Katz, L.F., Hall, R.E., & Eichengreen, B. (1992). Regional evolutions, *Brookings papers on economic activity, 1992*(1), 1-75.

Blau, F.D., & Kahn, L.M. (2017). The gender wage gap: Extent, trends, and explanations, *Journal of economic literature*, *55*(3), 789-865.

Bloom, N., & Van Reenen, J. (2007). Measuring & explaining management practices across firms & countries, *The Quarterly Journal of Economics, 122*(4), 1351-1408.

Bloom, N., & Van Reenen, J. (2010). Why do management practices differ across firms & countries? *Journal of economic perspectives, 24*(1), 203-24.

Bloom, N., & Van Reenen, J. (2011). Human resource management & productivity. In *Handbook of labor economics* (Vol. 4, pp. 1697-1767). Elsevier.

Bloom, N., Garicano, L., Sadun, R., & Van Reenen, J. (2014). The distinct effects of information technology & communication technology on firm organization, *Management Science, 60*(12), 2859-2885. https://doi.org/10.1287/mnsc.2014.2013.

Borjas, G.J. (2003). The labor demand curve is downward sloping: Re-examining the impact of immigration on the labor market, *The Quarterly Journal of Economics, 118*(4), 1335-1374. Retrieved from https://www.jstor.org/stable/25053941.

Börner, K., Scrivner, O., Gallant, M., Ma, S., Liu, X., Chewning, K., … Evans, J.A. (2018). Skill discrepancies between research, education, & jobs reveal the critical need to supply soft skills for the data economy. *Proceedings of the National Academy of Sciences of the United States of America, 115*(50), 12630–12637. https://doi.org/10.1073/pnas.1804247115.

Bosma, N., Van Praag, M., Thurik, R., & De Wit, G. (2004). The value of human & social capital investments for the business performance of start-ups, *Small Business Economics, 23*(3), 227-236.

Botsman, R., & Rogers, R. (Eds.) (2010). *What's mine is yours – The rise of collaborative consumption.* New York: HarperCollins Publishers.

Bound, J., Braga, B., Golden, J.M., & Khanna, G. (2015). Recruitment of foreigners in the market for computer scientists in the United States, *Journal of Labor Economics, 33(*S1), S187–S223. https://doi.org/10.1086/679020.

Bound, J., Khanna, G., & Morales, N. (2018). Understanding the economic impact of the H-1B program on the U.S. In G. H. Hanson, W. R. Kerr, & S. Turner (Eds.), *High-skilled migration to the United States & its economic consequences* (pp. 109–175). Retrieved from http://www.nber.org/chapters/c13842

Bourke, J., & Roper, S. (2017). Innovation, quality management & learning: Short-term & longer-term effects, *Research Policy, 46*(8), 1505-1518.

Brücker, H., Glitz, A., Lerche, A., & Romiti, A. (2021). Occupational recognition & immigrant labor market outcomes, *Journal of Labor Economics, 39*(2), 497–525. https://doi.org/10.1086/710702.

Brynjolfsson, E., & McAfee, A. (2011). *Race Against the Machine. How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Lexington/Massachusetts: Digital Frontier Press.

Brynjolfsson, E., & McAfee, A. (Eds). (2014). *The second machine age: Work, progress, & prosperity in a time of brilliant technologies.* London & New York: W W Norton & Co.

Brynjolfsson, E., Rock, D., & Syverson, C., (2020). The productivity J-Curve: How intangibles complement General Purpose Technologies, *American Economic Journal: Macroeconomics*. Forthcoming.

Bryson J.R., (Ed.) (2009). *Hybrid Manufacturing Systems & Hybrid Products: Services, Production & Industrialisation*. Aanchen: University of Aanchen.

Büchi, G., Cugno, M., & Castagnoli, R. (2020). Smart factory performance & Industry 4.0, *Technological Forecasting & Social Change, 150,* 1-10.

Buera, F.J., & Kaboski, J.P. (2012). The rise of the service economy, *American Economic Review, 102*(6), 2540-69.

Bughin J., Seong J., Manyika J., Chui M., & Joshi R., (2018). Notes from the AI frontier: Modeling the impact of AI on the world economy. *Discussion paper*, McKinsey Global Institute.

Burstein, A., Hanson, G., Tian, L., & Vogel, J. (2020). Tradability & the Labor-Market Impact of Immigration: Theory & Evidence From the United States, *Econometrica, 88*(3), 1071–1112. https://doi.org/10.3982/ecta16196.

Burstein, A., Morales, E., & Vogel, J. (2019). Changes in between-group inequality: Computers, occupations, & international trade, *American Economic Journal: Macroeconomics, 11*(2), 348-400. https://doi.org/10.1257/mac.20170291.

Burzyński, M. (2020). Labor market sorting: The medium-term economic impact of COVID-19. *LISER Working Paper No 2020-13*. https://doi.org/10.2139/ssrn.3750831.

Burzyński, M., & Gola, P. (2020). Mexican migration to the United States: Selection, assignment, & welfare. *Luxembourg Institute of Socio-Economic Research (LISER) Working Paper Series, 10*. https://doi.org/10.2139/ssrn.3422742.

Cadena, B.C., & Kovak, B.K. (2016). Migrants equilibrate local labor markets: Evidence from the Great Recession, *American Economic Journal: Applied Economics, 8*(1), 257–290. Retrieved from http://www.jstor.com/stable/24739078.

Capello, R., & Lenzi, C. (2021a). The Regional Economics of Technological Transformations – *Industry 4.0 & Servitisation in European regions.* London: Routledge.

Capello, R., & Lenzi, C. (2021b). Industry 4.0 & servitisation: Regional patterns of 4.0 technological transformations in Europe, *Technological Forecasting & Social Change, 173*, 1-14.

Capello, R., Camagni, R.P., Chizzolini, B., & Fratesi, U. (2008). *Modelling regional scenarios for the enlarged Europe: European competitiveness & global strategies.* Berlin (DE): Springer.

Capello, R., Caragliu, A., & Fratesi, U. (2015). Spatial heterogeneity in the costs of the economic crisis in Europe: are cities sources of regional resilience? *Journal of Economic Geography, 15*(5), 951–972.

Capello, R., Caragliu, A., & Fratesi, U. (2016). The costs of the economic crisis: which scenario for the European regions? *Environment & Planning C: Government & Policy, 34*(1), 113–130.

Capello, R., Caragliu, A., & Fratesi, U. (2017). Modeling regional growth between competitiveness & austerity measures: The MASST3 model, *International Regional Science Review, 40*(1), 38-74.

Capello, R., Caragliu, A., & Fratesi, U. (2018). The regional costs of market size losses in a EU dismembering process, *Papers in Regional Science, 97* (1), 73–90.

Cappelen, A., Castellacci, F., Fagerberg, J., & Verspagen, B. (2003). The impact of EU regional support on growth and convergence in the European Union, *JCMS: Journal of Common Market Studies, 41*(4), 621-644.

Card, D., Cardoso, A.R., & Kline, P. (2016). Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women, *The Quarterly journal of economics*, *131*(2), 633-686.

Card, D., Cardoso, A.R., Heining, J., & Kline, P. (2018). Firms and labor market inequality: Evidence and some theory, *Journal of Labor Economics*, *36*(S1), S13-S70.

Cardinaleschi, S., Damiani, M., & Pompei, F. (2020). Knowledge-intensive sectors & the role of collective performance-related pay, *Industry & Innovation, 27*(5), 480-512.

Carrillo-Tudela, C., Hobijn, B., She, P., & Visschers, L. (2016). The extent & cyclicality of career changes: Evidence for the U.K., *European Economic Review, 84,* 18–41. https://doi.org/10.1016/j.euroecorev.2015.09.008.

Castellacci, F., & Tveito, V. (2018). Internet use & well-being: A survey & a theoretical framework. *Research Policy, 47*(1), 308–325. https://doi.org/10.1016/j.respol.2017.11.007.

Castex, G., & Dechter, E.K. (2014). The changing roles of education and ability in wage determination, *Journal of Labor Economics 32(4)*, 685–710.

Cattaneo, C., Fiorio, C.V., & Peri, G. (2015). What Happens to the Careers of European Workers When Immigrants Take Their Jobs? *Journal of Human Resources, 50*(3), 655–693. https://doi.org/10.3368/JHR.50.3.655.

CEC – Commission of the European Communities (2004a). *Foresight & the Transition to Regional Knowledge-Based Economies,* Synthesis Report. Brussels: DG for Research Information & Communication Unit.

Cedefop (2012). Preventing skill obsolescence - Briefing note. *Briefing Note*, 1–4.

Cedefop (2017). People, machines, robots & skills. *Briefing Note*, (July), 1–4.

Cenamor, J., Sjodin, D.R., & Parida, V. (2017). Adopting a platform approach in servitization: leveraging the value of digitalization, *International Journal of Production Economics, 192*, 54-65.

Chuang, S. (2020). An empirical study of displaceable job skills in the age of robots, *European Journal of Training & Development,* (Online first). https://doi.org/10.1108/EJTD-10-2019-0183.

Ciffolilli, A., & Muscio, A. (2018). Industry 4.0: National & Regional Comparative Advantages in Key Enabling Technologies, *European Planning Studies, 26* (12), 2323-2343.

Cirillo, V., Sostero, M., & Tamagni, F. (2017). Innovation and within-firm wage inequalities: empirical evidence from major European countries, *Industry and Innovation*, *24*(5), 468-491.

Colombo, E., Mercorio, F., & Mezzanzanica, M. (2019). AI meets labor market: Exploring the link between automation & skills. *Information Economics & Policy, 47*, 27–37. https://doi.org/10.1016/j.infoecopol.2019.05.003.

Constantine, J., & Neumark, D. (1996). Training & the Growth of Wage Inequality. Industrial Relations, *A Journal of Economy & Society, 35,* 491-510.

Cortes, G.M. (2016). Where have the middle-wage workers gone? A study of polarization using panel data, *Journal of Labor Economics, 34(*1), 63–105. https://doi.org/10.1086/682289.

Costinot, A., & Vogel, J. (2015). Beyond Ricardo: Assignment models in international trade, *Annual Review of Economics, 7*(1), 31–62. https://doi.org/10.1146/annurev-economics-080213-041435.

Costrell, R.M., & Loury, G.C. (2004). Distribution of ability & earnings in a hierarchical job assignment model, *Journal of Political Economy, 112(*6), 1322–1363. https://doi.org/10.1086/424741.

Cotofan, M., De Neve, J.-E., Golin, M., Kaats, M., & Ward, G. (2021). Work & well-being during COVID-19: Impact, inequalities, resilience, & the future of work. In *World Happiness Report 2021* (p. Chapter 7).

Coupe, T. (2019). Automation, job characteristics & job insecurity. *International Journal of Manpower, 40*(7), 1288–1304. https://doi.org/10.1108/IJM-12-2018-0418.

Crespo Cuaresma, J., Ritzberger-Grünwald, D., & Silgoner, M.A. (2008). Growth, convergence and EU membership, *Applied Economics, 40*(5), 643-656.

Cusumano, M.A., Kahl, S.J., Suarez, F.F. (2015). Services, industry evolution, & the competitive strategies of product firms, *Strategic Management Journal, 36*(4), 559–575.

D'Amuri, F., & Peri, G. (2014). Immigration, jobs, & employment protection: evidence from Europe before & during the great recession, *Journal of the European Economic Association, 12*(2), 432-464. Retrieved from https://www.jstor.org/stable/24538833.

Dachs, B., Biege, S., Borowiecki, M., Lay, G., Jäger, A., & Schartinger, D. (2014). Servitisation of European Manufacturing: Evidence from a Large Scale Database, *Service Industries Journal, 34*(1), 5-23.

Damiani, M., Pompei, F., & Ricci, A. (2016). Performance related pay, productivity & wages in Italy: a quantile regression approach, *International Journal of Manpower, 37*(2), 344-371.

Damiani, M., Pompei, F., & Ricci, A. (2018). Family Firms & Labor Productivity: The Role of Enterprise-Level Bargaining in the Italian Economy, *Journal of Small Business Management, 56*(4), 573-600.

Damioli, G., Van Roy, V. & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity, *Eurasian Business Review, 11*, 1–25.

Dao, M., Furceri, D., & Loungani, M.P. (2014). Regional labor market adjustments in the United States and Europe. *International Monetary Fund*.

Dao, M.C., Das, M., Koczan, Z., & Lian, W. (2017). Why is labor receiving a smaller share of global income? theory and empirical evidence. *International Monetary Fund*.

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The adjustment of labor markets to robots, *Journal of the European Economic Association*, (Forthcoming). https://doi.org/10.1093/jeea/jvab012.

Davidsson, P., & Honig, B. (2003). The role of social & human capital among nascent entrepreneurs, *Journal of Business Venturing, 18,* 301-330.

De Groen, W.P., Lenaerts, K., Bosc, R., & Paquier, F. (2017). Impact of digitalisation & the on-demand economy on labour markets & the consequences for employment & industrial relations. *Employers' Group of the European Economic & Social Committee*. Retrieved from https://www.eesc.europa.eu/resources/docs/qe-02-17-763-en-n.pdf.

De La Rica, S., Gortazar, L., & Lewandowski, P. (2020). Job tasks & wages in developed countries: Evidence from PIAAC. *Labour Economics, 65*(August). https://doi.org/10.1016/j.labeco.2020.101845.

Deming, D.J. (2017). The growing importance of social skills in the labor market, *Quarterly Journal of Economics 132(4)*, 1593–1640.

De Propris, L., & Bailey, D. (Eds.) (2020). *Industry 4.0 & Regional Transformations*. London: Routledge.

De Propris, L., & Storai, D. (2019). Servitizing industrial regions, *Regional Studies, 53*(3), 388-397.

de Vries, G.J., Gentile, E., Miroudot, S., & Wacker, K.M. (2020). The rise of robots & the fall of routine jobs. *Labour Economics, 66*(June), 101885.https://doi.org/10.1016/j.labeco.2020.101885.

Del Rio-Chanona, R.M., Mealy, P., Beguerisse-Díaz, M., Lafond, F., & Farmer, J. D. (2021). Automation & occupational mobility: A data-driven network model, *Journal of the Royal Society Interface, 18*(20200898), 1–4. https://doi.org/10.1098/rsif.2020.0898.

Delaney, Judith M., & Paul J. Devereux. 2019. Understanding Gender Differences in STEM: Evidence from College Applications *Economics of Education Review 72* (October): 219–38. https://doi.org/10.1016/j.econedurev.2019.06.002.

Deming, D.J., & Kahn, L.B. (2018). Skill requirements across firms & labor markets: Evidence from job postings for professionals, *Journal of Labor Economics, 36*(S1), S337–S369. https://doi.org/10.1086/694106.

Deming, D.J., & Noray, K. (2020). Earnings dynamics, changing job skills, & STEM careers, *The Quarterly Journal of Economics, 135*(4), 1965–2005. https://doi.org/10.1093/qje/qjaa021.

Deming, D.J. (2017). The Growing Importance of Social Skills in the Labor Market, *The Quarterly Journal of Economics, 132* (4): 1593–1640. https://doi.org/10.1093/qje/qjx022.

Djumalieva, J., & Sleeman, C. (2018). An open & data-driven taxonomy of skills extracted from online job adverts. In C. Larsen, S. Rand, A. Schmid, & A. Dean (Eds.), *Developing skills in a changing world of work: Concepts, measurement & data applied in regional & local labour market* (pp. 425–454). https://doi.org/10.5771/9783957103154-425.

Dolan, P., & Lordan, G. (2020). Climbing up ladders & sliding down snakes: an empirical assessment of the effect of social mobility on subjective wellbeing. *Review of Economics of the Household.* https://doi.org/10.1007/s11150-020-09487-x.

Domini, G., Grazzi, M., Moschella, D., & Treibich, T. (2021). Threats & opportunities in the digital era : automation spikes, trade & employment dynamics, *Research Policy, 50(*7), 104137. https://doi.org/10.1016/j.respol.2020.104137.

Dosi, G., & Nelson, R.R. (2010). Technical change & industrial dynamics as evolutionary processes. In *Handbook of the Economics of Innovation* (Vol. 1, pp. 51-127). North-Holland.

Dosi, G., Guarascio, D., Ricci, A., & Virgillito, M.E. (2018). *Neodualism in the Italian business firms: training, organizational capabilities & productivity distributions.* Inapp WP No 1.

Dosi, G., Nelson, R.R., Winter, S. (eds.) (2000). *The Nature & Dynamics of Organizational Capabilities*. Oxford/New York, Oxford University Press

Drahokoupil, J., & Piasna, A. (2017). Work in the Platform Economy: Beyond Lower Transaction Costs, Intereconomics – *Review of European Economic Policy,* https://www.intereconomics.eu/contents/year/2017/number/6/article/work-in-the-platform-economy-beyond-lower-transaction-costs.html (Retrieved 16/11/2021).

Dupuy, A. (2015). The assignment of workers to tasks with endogenous supply of skills, *Economica*, *82*(325), 24–45. Retrieved from https://www.jstor.org/stable/24751946.

Dworkin, J.D. (2019). Network-driven differences in mobility & optimal transitions among automatable jobs, *Royal Society Open Science, 6*(7). https://doi.org/10.1098/rsos.182124.

EBRD (2018). *Work in Transition: Transition Report 2018-2019*. European Bank for Reconstruction and Development.

EC (2021). *The Digital Economy and Society Index* (DESI) 2021, available at https://digital-strategy.ec.europa.eu/en/library/digital-economy-and-society-index-desi-2021, last accessed 03/02/2022.

Edin, P.-A., Fredriksson, P., Nybom, M., & Ockert, B. (2017). The rising return to non-cognitive skill.¨

Institute of Labor Economics (IZA).

Edquist, H., Goodridge, P., & Haskel, J. (2019). The Internet of Things & economic growth in a panel of countries. *Economics of Innovation & New Technology, Forthcoming*. URL https://doi.org/10. 1080/10438599.2019.1695941.

Eggenberger, C., Rinawi, M., & Backes-Gellner, U. (2018). Occupational specificity: A new measurement based on training curricula & its effect on labor market outcomes. *Labour Economics, 51,* 97–107. https://doi.org/10.1016/j.labeco.2017.11.010.

Eloranta V., & Turunen, T. (2016). Platforms in service-driven manufacturing: leveraging complexity by connecting, sharing, & integrating, *Industrial Marketing Management, 55,* 178-186.

Ernst, E., Merola, R., & Samaan, D. (2018). The economics of artificial intelligence: Implications for the future of work. *International Labour Organization Research Paper*, (2018–5).

Eurofound. (2018). Game changing technologies: Exploring the impact on production processes & work. Luxembourg: Publications Office of the European Union. https://doi.org/10.2806/36769.

EU Commission (2012). *Knowledge Intensive (Business) Services in Europe.* Brussels.

EU Commission (2019a). *Co-design towards the first strategic plan for Horizon Europe. A report on the web-based consultation and on the European Research and Innovation Days*. Brussels: Research&Innovation.

European Commission (2020). *Digital Education Action Plan 2021-2027.* European Commission, 20.

Evans, S., & Schmalensee, R. (Eds.) (2016). *Matchmakers – The New Economics of Multisided Platforms.* Boston, Massachusetts: Harvard Business Review Press.

Fagerberg, J., Mowery, D.C., & Nelson, R.R. (Eds.) (2005). *The Oxford handbook of innovation.* Oxford university press.

Faggian, A., Rajbhandari, I., & Dotzel, K.R. (2017). The interregional migration of human capital & its regional consequences: a review. *51*(1), 128–143. https://doi.org/10.1080/00343404.2016.1263388

Favell, A. (2008). The newface of east-west migration in europe. *Journal of ethnic & migration studies 34*(5), 701–716.

Fernández-Macías, E., & Bisello, M. (2020). A taxonomy of tasks for assessing the impact of new technologies on work. *Joint Research Centre – European Commission – Eurofound Technical Report 04.*

Felipe, J., Bajaro, D., Estrada, G., & McCombie, J. (2020). The relationship between technical progress and employment: A comment on autor and salomons. *Levy Economics Institute Working Paper 946*.

Felipe, J., & McCombie, J. (2019). The illusions of calculating total factor productivity and testing growth models: From cobb-douglas to solow and romer. *ADB Economics Working Paper 596*.

Feyrer, J. (2007). Demographics & productivity, *Review of Economics & Statistics 89*(1), 100–109.

Fillmore, Ian, and Jonathan D. Hall. 2021. 'Technological Change and Obsolete Skills: Evidence from Men's Professional Tennis'. *Labour Economics* 73 (September): 102051. https://doi.org/10.1016/j.labeco.2021.102051.

Firpo, S., Fortin, N.M., & Lemieux, T. (2011). Occupational tasks & changes in the wage structure*. IZA Discussion Paper No 5542.*

Fitzenberger, B., & Kunze, A. (2005). Vocational training & gender: Wages & occupational mobility among young workers, *Oxford Review of Economic Policy, 21*(3), 392–415. https://doi.org/10.1093/oxrep/gri023

Foged, M., & Peri, G. (2016). Immigrants' effect on native workers: New analysis on longitudinal data, *American Economic Journal: Applied Economics, 8*(2), 1–34. Retrieved from https://www.jstor.org/stable/24739100

Fossen, F. M., & Sorgner, A. (2019). New digital technologies & heterogeneous employment & wage dynamics in the United States: Evidence from individual-level data. *IZA Discussion Paper Series No 12242.*

Frank, M.R., Sun, L., Cebrian, M., Youn, H., & Rahwan, I. (2018). Small cities face greater impact from automation. *Journal of the Royal Society Interface, 15*(139). 1–52. https://doi.org/10.1098/rsif.2017.0946.

Frenken, K., & Schor, J. (2017). Putting the Sharing Economy into Perspective, *Environmental Innovation & Societal Transition, 23*, 3-10.

Frenken, K. (2017). Political Economies & Environmental Futures for the Sharing Economy, *Philosophical Transaction A, 375*, 1-15.

Frenken, K., Meelen, T., Arets, M., & Van de Glind, P. (2015). Smarter Regulation for the Sharing Economy, *The Guardian*, https://www.theguardian.com/science/political-science/2015/may/20/smarter-regulation-for-the-sharing-economy (Retrieved 16/11/2021).

Frey, C.B., & Osborne, M.A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting & Social Change, 114*, 254-280.

Gathmann, C., & Schönberg, U. (2010). How general is human capital? A task-based approach, *Journal of Labor Economics, 28*(1), 1–49. https://doi.org/10.1086/649786.

Gathmann, C., Helm, I., & Schönberg, U. (2020). Spillover effects of mass layoffs, *Journal of the European Economic Association, 18*(1), 427–468. https://doi.org/10.1093/jeea/jvy045.

Gebauer, H., Paiola, M., Saccani, N., & Rapaccini, M. (2021). Digital servitization: Crossing the perspectives of digitization & servitization, *Industrial Marketing Management, 93*, 382-388.

Geel, R., & Backes-Gellner, U. (2011). Occupational mobility within & between skill clusters: An empirical analysis based on the skill-weights approach, *Empirical Research in Vocational Education & Training, 3*(1), 21–38. https://doi.org/10.1007/bf03546496.

Ghodsi, M., Reiter, O., Stehrer, R., & Stöllinger, R. (2019). Robotisation, employment and industrial growth intertwined across global value chains. *wiiw Working Paper 177*.

Giabelli, A., Malandri, L., Mercorio, F., & Mezzanzanica, M. (2020). GraphLMI: A data driven system for exploring labor market information through graph databases. *Multimedia Tools & Applications*, (Online first). https://doi.org/10.1007/s11042-020-09115-x.

Giabelli, A., Malandri, L., Mercorio, F., Mezzanzanica, M., & Seveso, A. (2020). NEO: A tool for taxonomy enrichment with new emerging occupations. *International Semantic Web Conference, LNCS 12507, 568–584.*

Gibbons, R., & Roberts, J. (2013). *The handbook of organizational economics*, New Jersey, USA: Princeton University Press.

Gihleb, R., Giuntella, O., Stella, L., & Wang, T. (2020). Industrial robots, workers' safety, & health. IZA *Discussion Paper No 13672.*

Giorcelli, M. (2019). The long-term effects of management & technology transfers. *American Economic Review, 109*(1), 121–152. https://doi.org/https://doi.org/10.1257/aer.20170619.

Gola, P. (2021). Supply & demand in a two-sector matching model, *Journal of Political Economy, 129*(3), 940–978. https://doi.org/10.1086/712507.

Goldin, C. (2014). A Grand Gender Convergence: Its Last Chapter, *American Economic Review, 104*(4), 1091-1119. http://dx.doi.org/10.1257/aer.104.4.1091.

Goldin,C., & Katz, L.F. (2009). *The Race Between Education and Technology.* Cambridge/ Massachusetts: Harvard University Press.

Gomes, E., Bustinza, O.F., Tarba, S., Khan, Z., & Ahammad, M. (2019). Antecedents & implications of territorial servitization, *Regional Studies, 53(*3), 410-423.

Goolsbee, A. (2018). Public policy in an AI economy. *NBER Working Paper Series No 24653*. Retrieved from http://www.nber.org/papers/w24653.

Goos, M., Arntz, M., Zierahn, U., Gregory, T., Gomez, S.C., Vazquez, I.G., & Jonkers, K. (2019). The impact of technological innovation on the future of work. *Joint Research Centre Working Papers: Series on Labour, Education and Technology*.

Goos, M., & Manning, A. (2007). Lousy and lovely jobs: the rising polarization of work in Britain, *The Review of Economics and Statistics 89(1)*, 118–133.

Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in europe, *American Economic Review 99(2)*, 58–63.

Goos, M., Manning, A., & Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring, *American Economic Review 104* (8): 2509–26. https://doi.org/10.1257/aer.104.8.2509.

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

Gregory, T., Salomons, A., & Zierahn, U. (2021). Racing with or against the machine? Evidence on the role of trade in Europe, *Journal of the European Economic Association*, no. jvab040. https://doi.org/10.1093/jeea/jvab040.

Griffin, P., McGaw, B., & Care, E. (2012). *Assessment & teaching of 21st century skills*. Springer.

Groes, F., Kircher, P., & Manovskii, I. (2013). The U-shapes of occupational mobility. *Review of Economic Studies, 82*(2), 659–692. https://doi.org/10.1093/restud/rdu037.

Gunadi, C., & Ryu, H. (2021). Does the rise of robotic technology make people healthier*? Health Economics, Forthcoming*. https://doi.org/10.1002/hec.4361.

Guren, A., Hémous, D., & Olsen, M. (2015). Trade dynamics with sector-specific human capital. *Journal of International Economics, 97*(1), 126–147. https://doi.org/10.1016/j.jinteco.2015.04.003.

Hansen, A. (1938). Economic progress & the declining population growth, *American Economic Review 29*(1), 1–15.

Hawkins, J. (2001). Economic Forecasting: History & Procedures, *mimeo* available on line.

Helfat, C.E., & Martin, J.A. (2015). Dynamic managerial capabilities: Review & assessment of managerial impact on strategic change, *Journal of management, 41(*5), 1281-1312.

Hendry, D., & Clements, M.P. (2001). Economic Forecasting: Some Lessons from Recent Research, *mimeo* available on-line

Hershbein, B., & Kahn, L. B. (2018). Do recessions accelerate routine-biased technological change? Evidence from vacancy postings, *American Economic Review, 108*(7), 1737–1772. https://doi.org/10.1257/aer.20161570.

Humlum, A. (2019). Robot adoption & labor market dynamics. Working Paper Princeton University.

IMF (2018). *Measuring the digital economy*. IMF Staff Working Paper.

Jaimovich, N., & Siu, H.E. (2018). High-skilled immigration, STEM employment, & non-routine-biased technical change. In G. H. Hanson, W. R. Kerr, & S. Turner (Eds.), *High-skilled migration to the United States & its economic consequences* (pp. 177–204). Retrieved from http://www.nber.org/chapters/c13845%0D.

Jauer, J., Liebig, T., Martin, J.P., & Puhani, P.A. (2019). Migration as an adjustment mechanism in the crisis? A comparison of Europe and the United States 2006–2016, *Journal of Population Economics, 32*(1), 1-22.

Jerbashian, V. (2019). Automation & job polarization: on the decline of middling occupations in *Europe. Oxf. Bull. Econ. Stat. 81,* 1095–1116.

Jestl, S. (2022). Industrial robots, and information and communication technology: The employment effects in EU labour markets. *wiiw Working Paper forthcoming*.

Jestl, S., Landesmann, M., & Leitner, S.M. (2015). *Migrants & Natives in EU Labour Markets: Mobility & Job-Skill Mismatch Patterns.* https://www.econstor.eu/handle/10419/204175.

Kaltenberg, M., & Foster-McGregor, N. (2022). The impact of automation on inequality across europe. *forthcoming*.

Kaplan, S. (2008). Cognition, capabilities, & incentives: Assessing firm response to the fibre-optic revolution, *Academy of Management Journal, 51,* 672-695.

Kartha, C.P. (2004). A comparison of ISO 9000: 2000 quality system standards, QS9000, ISO/TS 16949 & Baldrige criteria. *The TQM magazine.*

Kenney, M., & Zysman, J. (2016). The Rise of the Platform Economy, *Issues in Science & Technology, 32*(3).

Keynes, J.M. (1930). *Essays in Persuasion*, Chapter Economic Possibilities for our Grandchildren.

358–373. New York: Harcourt Brace.

Kerr, S.P., Kerr, W., Özden, C., & Parsons, C. (2016). Global talent flows. In Journal of Economic Perspectives (Vol. 30, Issue 4, pp. 83–106). *American Economic Association.* https://doi.org/10.1257/jep.30.4.83.

Kerr, S.P., Kerr, W., Özden, Ç., & Parsons, C. (2017). High-skilled migration & agglomeration. In Annual Review of Economics (Vol. 9, pp. 201–234). *Annual Reviews Inc.* https://doi.org/10.1146/annurev-economics-063016-103705.

King, M., Lambert, R., & Temple, P. (2017). Measurement, standards & productivity spillovers. In *Handbook of Innovation & Standards.* Edward Elgar Publishing.

Klenert, D., Fernandez-Macias, E., & Anton, J.-I. (2020). Do robots really destroy jobs? Evidence from Europe (No. 2020–01; *JRC Working Papers on Labour, Education & Technology).* https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/do-robots-really-destroy-jobs-evidence-europe.

Koch, M., Manuylov, I., & Smolka, M. (2019). Robots & firms. *CESifo Working Paper Series No. 7608,* (April).

Kohtamäki, M., Baines, T., Rabetino, R., Bigdeli, A.Z., Kowalkowski, C., Oliva, R., & Parida, V. (2021). *The Palgrave Handbook of Servitization*, Springer, Cham, Switzerland.

Kohtamäki, M., Parida, V., Oghazi, P., Gebauer, H., & Baines, T. (2019). Digital servitization business models in ecosystems: a theory of the firm, *Journal of Business Research, 104*, 380–392.

Kohtamäki, M., Parida, V., Patel, P.C., & Gebauer, H. (2020). The relationship between digitalization & servitization: the role of servitization in capturing the financial potential of digitalization, *Technological Forecasting & Social Change, 151,* https://doi.org/10.1016/j.techfore.2019.119804.

Konings, J., & Vanormelingen, K. (2015). The Impact of Training on Productivity & Wages: Firm-Level Evidence, *The Review of Economics & Statistics, 97* (2), 485–497.

Korkeamäki, O., & Kyyrä, T. (2006). A gender wage gap decomposition for matched employer–employee data, *Labour Economics*, *13*(5), 611-638.

Kornberger, M., Pflueger, D., & Mouritsen, J. (2017). Evaluative infrastructures: Accounting for platform organization, *Accounting, Organization & Society, 60,* 79-95.

Koutsimpogiorgos, N., van Slageren, J., Herrmann, A.M., & Frenken, K. (2020). Conceptualizing the Gig Economy & Its Regulatory Problems, *Policy & Internet, 12*(4), 525-545.

Kroft, K., & Pope, D.G. (2014). Does online search crowd out traditional search & improve matching efficiency? Evidence from Craigslist, *Journal of Labor Economics, 32*(2), 259–303. https://doi.org/10.1086/673374

Kromann, L., & Sørensen, A., (2020). Automation, performance & international Competition: A firm-level comparison of process innovation, *Economic Policy 34*, 691–722. URL https://doi.org/10.1093/epolic/eiaa002.

Kromann, L., Malchow-Møller, N., Skaksen, J.R., & Sørensen, A., (2019). Automation & productivity? A Cross-country, cross-industry comparison, *Industrial & Corporate Change, 29,* 265–287. URL https://doi.org/10.1093/icc/dtz039.

Krueger, A.B. (1993). How computers have changed the wage structure: evidence from microdata, 1984-1989, *The Quarterly Journal of Economics, 108(1)*, 33–60.

Krusell, P., Ohanian, L.E., Rios-Rull, J.-V., & Violante, G.L. (2000). Capital-skill complementarity and inequality: A macroeconomic analysis, *Econometrica, 68(5)*, 1029–1053.

LafuenteE., Vaillant, Y., & Vendrell-Herrero, F. (2019). Territorial Servitization & the Manufacturing Renaissance in Knowledge-based Economies, *Regional Studies, 53(*3), 313-319.

Lafuente, E., Vaillant, Y., Vendrell-Herrero, F. (2017). Territorial servitization: Exploring the virtuous circle connecting knowledge-intensive services & new manufacturing businesses, *International Journal of Production Economics, 192*, 19-28.

Lamb, C., Huynh, A., & Vu, V. (2019). Lost and found: Pathways from disruption to employment. *Brookfield Institute Report.*

Lane, M., & Saint-Martin, A. (2021). The impact of Artificial Intelligence on the labour market : What do we know so far ? *OECD Social, Employment & Migration Working Papers Series No 256.* https://doi.org/10.1787/7c895724-en.

Lasi, H., Fettke, P., Kemper, H-G., Feld, T., & Hoffmann, M. (2014). Application-Pull & Technology-Push as Driving Forces for the Fourth Industrial Revolution, *Business & Information Systems Engineering, 6*, 239–242.

Lazear, E.P., & Rosen, S. (1981). Rank-order Tournaments as Optimum Labor Contracts, *Journal of Political Economy,* 89, 841–864.

Lazear, E.P. (1986). Salaries and Piece Rates, *The Journal of Business* 59, 405–31.

Lazear, E.P. (2009). Firm-specific human capital: A skill-weights approach, *Journal of Political Economy, 117(*5), 914–940. https://doi.org/10.1086/648671.

Leitner, S., Stehrer, R., & Grieveson, R. (2019). Eu faces a tough demographic reckoning. *wiiw Policy Note/Policy Report 30*.

Leitner, S.M., & Stehrer, R. (2019a). The automatisation challenge meets the demographic challenge: In need of higher productivity growth*. ECFIN Discussion papers (117).*

Leitner, S.M., & Stehrer, R. (2019b). Demographic challenges for labour supply & growth. *wiiw Working Papers (439).*

Lewandowski, P., Keister, R., Hardy, W., Górka, S. (2020). Ageing of routine jobs in Europe, *Economic Systems, 44* (4)

Lewandowski, P., Park, A., Hardy, W., & Du, Y. (2019). Technology, skills, & globalization: Explaining international differences in routine & nonroutine work using survey data. *SSRN Electronic Journal, (12339*). https://doi.org/10.2139/ssrn.3415008

Lewandowski, P. *et al.* (2022). T*he drivers of income inequality in europe in the 21st century.* UNTANGLED, Deliverable 3.6.

Lin, G.C. (2019). High-skilled immigration & native task specialization in U.S. cities, *Regional Science & Urban Economics, 77*(June), 289–305. https://doi.org/10.1016/j.regsciurbeco.2019.06.004

Lind, T., & Malmberg, B. (1999). Age structure effects & growth in the OECD, *Journal of Population Economics, 12*(3), 431–449.

Loomis D.G., & Cox, J.E jr. (2000). A Course in Economic Forecasting: Rationale and Content, *Journal of Economic Education, 31*(4), 349-357.

Maestas, N., Mullen, K.J., & Powell, D. (2016). The effect of population aging on economic growth, the labor force & productivity. *NBER Working Paper 22452.*

Manning, A., & Saidi, F. (2010). Understanding the gender pay gap: what's competition got to do with it? *ILR Review*, *63*(4), 681-698.

Marcotte, D.E. (2000). Continuing Education, Job Training, & the Growth of Earnings Inequality, *ILR Review, 53*(4), 602-623.

Martin, L. (2017). Do innovative work practices & use of information & communication technologies motivate employees? *Industrial Relations, 56*(2), 263–292. https://doi.org/10.1111/irel.12173

Martin, L. (2020). How to retain motivated employees in their jobs*? Economic & Industrial Democracy, 41(*4), 910–953. https://doi.org/10.1177/0143831X17741528.

McAfee, A., & Brynjolfsson, E. (eds.) (2017). *Machine, Platform, Crowd: Harnessing Our Digital Future*. London & New York: W W Norton & Co.

McGuinness, S., Pouliakas, K., & Redmond, P. (2021). Skills-displacing technological change & its impact on jobs: Challenging technological alarmism? *Economics of Innovation & New Technology.* https://doi.org/10.1080/10438599.2021.1919517.

McGuirk, H., Lenihan, H., & Hart, M., (2015). Measuring the impact of innovative human capital on small firms' propensity to innovate, *Research Policy, 44*(4), 965-976.

McLaren, J. (2017). Globalization & labor market dynamics. In *Annual Review of Economic*s, *9*, 177-200. Annual Reviews Inc. https://doi.org/10.1146/annurev-economics-063016-103720.

Méda, D. (2016). The future of work: The meaning & value of work in Europe. *ILO Research Paper No 18.*

Menon, S., Salvatori, A., & Zwysen, W. (2020). The effect of computer use on work discretion & work intensity: Evidence from Europe, *British Journal of Industrial Relations, 58(*4), 1004-1038. https://doi.org/10.1111/bjir.12504

Meyersson Milgrom, E.M., Petersen, T., & Snartland, V. (2001). Equal pay for equal work? Evidence from Sweden and a comparison with Norway and the US, *Scandinavian Journal of Economics*, *103*(4), 559-583.

Michaels, G., Natraj, A., & van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years, *Review of Economics and Statistics, 96(1)*, 60–77.

Miles, I., & Keenan, M. (2000). *Foren Issue Paper - From National to Regional Foresight: Experiences & Methods,* workshop 1, Manchester, April.

Modestino, A.S., Shoag, D., & Ballance, J. (2016). Downskilling: changes in employer skill requirements over the business cycle, *Labour Economics, 41,* 333–347. https://doi.org/10.1016/j.labeco.2016.05.010.

Modestino, A.S., Shoag, D., & Ballance, J. (2020). Upskilling: Do employers demand greater skill when workers are plentiful? *The Review of Economics & Statistics, 102*(4), 793–805. https://doi.org/https://doi.org/10.1162/rest_a_00835.

Moroşanu, L., King, R., Lulle, A., & Pratsinakis, M. (2021). One improves here every day: 'the occupational & learning journeys of lower-skilled' European migrants in the London region, *Journal of Ethnic & Migration Studies, 47*(8), 1775–1792. https://doi.org/10.1080/1369183X.2019.1679411.

Müller, J.M., Buliga, O., & Voigt, K.I. (2018). Fortune Favours the Prepared: How SMEs Approach Business Model Innovations in Industry 4.0, *Technological Forecasting & Social Change, 132*(7), 2-17.

Murphy, K.J. (1999). Executive Compensation, *Handbook of Labor Economics,* 3, 2485–2563.

Neely, A. (2007). *The servitization of manufacturing: an analysis of global trends*. Paper presented at the 14th European Operations Management Association Conference. Ankara, Turkey, 17-19 June.

Nedelkoska, L., & Quintini, G. (2018). Automation, skills use and training. *OECD Social, Employment and Migration Working Papers 202*.

Niederberger, M., & Renn, O. (2019). *Delphi-Verfahren in den Sozial- und Gesundheits-wissenschaften.* Konzept, Varianten und Anwendungsbeispiele. Springer.

Nishioka, S., & Ripoll, M. (2012).Productivity, trade and the r&d content of intermediate inputs, *European Economic Review 56(8)*, 1573–1592.

Nonaka, I., Toyama, R., & Konno, N. (2000). SECI, Ba & leadership: a unified model of dynamic knowledge creation, *Long range planning, 33*(1), 5-34.

Nordhaus, W.D. (2020). Are we approaching an economic singularity? Information Technology & the future of economic growth, *American Economic Journal: Macroeconomics*, Forthcoming.

Norwegian Ministry of Education & Research. (2017). *Norwegian Strategy for Skills policy 2017-2021*.

OECD (2005). How persistent are regional disparities in employment? The role of geographic mobility. *OECD Employment Outlook 2005* (pp. 73-123). Paris: OECD Publishing.

OECD (2016). New skills for the digital economy: Measuring the demand & supply of ICT skills at work. *OECD Digital Economy Papers No 258*. https://doi.org/10.1787/5jlwz83z3wnw-en.

OECD (2017), Dare to Share: Germany's Experience Promoting Equal Partnership in Families. Paris: OECD Publishing. https://dx.doi.org/10.1787/9789264259157-en.

OECD (2019a). *The Future of Work*. OECD Employment Outlook 201.

OECD (2019b). *Measuring the Digital Transformation: A Roadmap for the Future*. Paris: OECD Publishing.

OECD. (2019c). *OECD Skills Strategy 2019: Skills to shape a better future.* OECD Report. https://doi.org/10.1787/9789264313835-en.

OECD (2019d). *Part-time and Partly Equal: Gender and Work in the Netherlands.* Paris: OECD Publishing. https://dx.doi.org/10.1787/204235cf-en.

OECD. (2020). *OECD Digital Economy Outlook 2020.* Paris: OECD Publishing. https://doi.org/10.1787/bb167041-en.

OECD. (2021a). *OECD Skills Outlook 2021: Learning for life.* OECD Report. https://doi.org/https://doi.org/10.1787/0ae365b4-en.

OECD (2021b). *The Role of Firms in Wage Inequality: Policy Lessons from a Large Scale Cross-Country Study.* Paris: OECD Publishing. https://doi.org/10.1787/7d9b2208-en.

Oesch, D., & Menés J.R. (2011). Upgrading or polarization? Occupational change in Britain, Germany, Spain and Switzerland, 1990-2008, *Socio-Economic Review 9(3)*, 503–531.

Opazo-Basáez, M., Vendrell-Herrero, F., & Bustinza, O.F. (2022). Digital service innovation: a paradigm shift in technological innovation, *Journal of Service Management, 33*(1), 97-133.

Ottaviano, G.I.P., & Peri, G. (2012). Rethinking the effect of immigration on wages, *Journal of the European Economic Association, 10(*1), 152–197. Retrieved from https://www.jstor.org/stable/41426727.

Overman, H.G., & Puga, D. (2002). Unemployment clusters across Europe's regions and countries, *Economic policy, 17*(34), 115-148.

Paiva Santos, B., Charrua-Santos, F., & Lima, T.M. (2018). *Industry 4.0: An Overview, Proceedings of the World Congress on Engineering*, Vol II, July 4-6, London, U.K.

Papageorgiou, T. (2014). Learning your comparative advantages, *Review of Economic Studies, 81*(3), 1263–1295. https://doi.org/10.1093/restud/rdt048.

Peri, G., & Sparber, C. (2009). Task specialization, immigration, & wages. *American Economic Journal: Applied Economics, 1(*3), 135–169. https://doi.org/10.1142/9781.

Peri, G., & Sparber, C. (2011). Highly educated immigrants & native occupational choice, *Industrial Relations, 50*(3), 385–411. https://doi.org/10.1111/j.1468-232X.2011.00643.x.

Pichler, D., & Stehrer, R. (2021). Is ICT still polarising labour demand after the crisis? *wiiw Working Paper 207*.

Pompei, F., Damiani, M., & Ricci, A. (2019). Family firms, performance-related pay, & the great crisis: evidence from the Italian case, *Industrial & Corporate Change, 28*(5), 1193-1225.

Pouliakas, K. (2018). Determinants of Automation Risk in the EU Labour Market: A Skills-Needs Approach. *IZA Discussion Papers No. 11829.*

Powell, C. (2003). The Delphi technique: myths & realities, *Journal of advanced nursing.* DOI: 10.1046/j.1365-2648.2003.02537.x

Prettner, K. (2019). A note on the implication of automation for economic growth & the labor share, *Macroeconomic Dynamics 23*(3).

Prettner, K.P., & Bloom, D.E. (2020). *Automation and Its Macroeconomic Consequences. Theory, Evidence and Social Impacts*. London: Elsevier.

Rabetino, R., Kohtamäki, M., Brax, S.A., & Sihvonen, J. (2021). The tribes in the field of servitization: Discovering latent streams across 30 years of research, *Industrial Marketing Management, 95*, 70-84.

Rahman, K.S., & Thelen, K. (2019). The Rise of the Platform Business Model & the Transformation of Twenty-First-Century Capitalism, *Politics & Society, 42*(2), 177-204.

Rebollo-Sanz, Y.F., & De la Rica, S. (2020). Gender Gaps in Skills & Labor Market Outcomes: Evidence from the PIAAC, *Review of Economics of the Household*, November. https://doi.org/10.1007/s11150-020-09523-w.

Ricardo, D. (1821). *On the Principles of Political Economy and Taxation* (3 ed.). London: John Murray.

Rifkin, J. (1995). *The End of Work: The Decline of the Global Labor Force and the Dawn of the Post-Market Era*.

Rinawi, M., & Backes-Gellner, U. (2021). Labour market transitions after layoffs: the role of occupational skills. *Oxford Economic Papers, 73*(1), 76–97. https://doi.org/10.1093/oep/gpz064.

Roy, A.D. (1951). Some thoughts on the distribution of earnings. *Oxford Economic Papers, 3*(2), 135–146. https://doi.org/https://doi.org/10.1093/oxfordjournals.oep.a041827.

Rullani, E., & Rullani, F., eds. (2018). *Dentro la rivoluzione digitale*. Giappicchelli: Torino.

Sachs, J., Benzell, S., & LaGarda, G. (2015). Robots: Curse or blessing? a basic framework. *NBER Working Paper 21091*.

Sachs, J., & Kotlikoff, L. (2012). Smart machines and long-term misery. *NBER Working Paper 18629*.

Sattinger, M. (1975). Comparative advantage & the distributions of earnings & abilities. *Econometrica, 43*(3), 455–468. Retrieved from https://www.jstor.org/stable/1914276.

Sattinger, M. (1979). Differential rents & the distribution of earnings, *Oxford Economic Papers, 31*(1), 60–71. https://doi.org/https://doi.org/10.1093/oxfordjournals.oep.a041437.

Schmidpeter, B., & Winter-Ebmer, R. (2018). How do automation & offshorability influence unemployment duration & subsequent job quality? *IZA Discussion Paper No 11736.*

Schor, J. (2016). Debating the Sharing Economy, *Journal of Self-Governance & Management Economics, 4(*3), 7-22.

Schor J.B., Walker E.T., Lee C.W., Parigi, P., & Cook, K. (2015). On the Sharing Economy, *Contexts, 14,* 12-19.

Schroder, M. (2020). Cognitive Skill Biased Technological Change, Income & Wealth Inequality in the UK. *Paper Presented at the 1st LISER/IAB Conference on Digital Transformation & the Future of Work, 13-14 Feb. 2020.*

Schulz, E., & Radvansky, M. (2014). Impact of ageing populations on silver economy, health & long-term care workforce. *NEUJOBS Policy Brief NO. D12.*4, (January).

Schwab, K., ed. (2017). *The Fourth Industrial Revolution*. Crown Publishing Group: New York.

Schwabe, H., & Castellacci, F. (2020). Automation, workers' skills & job satisfaction. *PLoS ONE*, *15*(11), 1–26. https://doi.org/10.1371/journal.pone.0242929.

Segovia-Pérez, M., Castro Núñez, R.B., Santero Sánchez, R., & Laguna Sánchez, P. (2020). Being a woman in an ICT job: An analysis of the gender pay gap and discrimination in Spain, *New Technology, Work and Employment*, *35*(1), 20-39.

Servoz, M. (2019). *AI. The Future of Work? Work of the Future! On how artificial intelligence, robotics and automation are transforming jobs and the economy in Europe*. Report for the European Commission.

Sforzi, F., & Boix, R. (2019). Territorial Servitization in Marshallian Industrial Districts: the Industrial Districts as a Place-based Form of Servitization, *Regional Studies, 53*(3), 398-409.

Sharpe, J., & Bollinger, C.R. (2020). Who competes with whom? Using occupation characteristics to estimate the impact of immigration on native wages. *Labour Economics, 66*, 101902. https://doi.org/10.1016/j.labeco.2020.101902.

Sisti, E., & Goena, A.Z. (2020). Panel analysis of the creation of new KIBS in Spain: The role of manufacturing & regional innovation systems (RIS), *Investigaciones Regionales-Journal of Regional Research, 48,* 37-50.

Sostero, M., Milasi, S., Hurley, J., Fernandez-Macías, E., & Bisello, M. (2020). Teleworkability & the COVID-19 crisis: a new digital divide? *JRC Technical Report*, 74.

Spitz-Oener, A. (2006). Technical change, job tasks, & rising educational demands: Looking outside the wage structure, *Journal of Labor Economics, 24*(2), 235–270. https://doi.org/10.1086/499972.

Srnicek, N., ed. (2016). *Platform Capitalism*, Polity Press: Cambridge & Malden.

Stanford, J. (2017). The resurgence of gig work: Historical & theoretical perspectives, *The Economic and Labour Relations Review, 28(3*), pp. 382-401.

Stehrer, R. (2022). Capital accumulation, total factor productivity, and employment growth: Mediumterm relations in a cross-section analysis. *DG ECFIN Discussion paper forthcoming*.

Stehrer, R. (2022b). *The impact of capital accumulation by asset types on labour demand and income distribution.* UNTANGLED, Deliverable 4.1.

Stehrer, R., Bykova, A., Jäger, K., Reiter, O., & Schwarzhappel, M. (2019). *Industry level growth and productivity data with special focus on intangible assets.* Technical report, The Vienna Institute for International Economic Studies.

Stehrer, R., & Tverdostup, M. (2022). *Demography, capital accumulation and growth.* UNTANGLED, Deliverable 3.2.

Stephany A., ed. (2015). *The Business of Sharing: Collaborative Consumption & Making it in the New Sharing Economy*. Palgrave Macmillan, Houndmills, Basingstoke, Hampshire, New York, NY.

Summers, L.H. (2013). *Why stagnation might prove to be the new normal.* The Financial Times.

Summers, L.H. (2020). Accepting the reality of secular stagnation: New approaches are needed to deal with sluggish growth, low interest rates & an absence of inflation, *Finance & Development 57*(1).

Teece, D.J. (2007). Explicating dynamic capabilities: the nature & microfoundations of (sustainable) enterprise performance, *Strategic management journal, 28*(13), 1319-1350.

Teece, D.J. (2010). Business models, business strategy & innovation, *Long range planning, 43*(2-3), 172-194.

Teece, D.J. (2016). Dynamic capabilities & entrepreneurial management in large organizations: Toward a theory of the (entrepreneurial) firm, *European Economic Review, 86,* 202-216.

Tegmark, M. (2017). *Life 3.0: Being Human in the Age of Artificial Intelligence*. New York: Alfred A. Knopf.

Terziovski, M., & Guerrero, J.L. (2014). ISO 9000 quality system certification & its impact on product & process innovation performance, *International Journal of Production Economics, 158*, 197-207.

Teulings, C., & Baldwin, R. (2014). *Secular Stagnation: Facts, Causes and Cures*. CEPR Pres.

Teulings, C.N. (1995). The wage distribution in a model of the assignment of skills to jobs, *Journal of Political Economy, 103*(2), 280–315. Retrieved from https://www.jstor.org/stable/2138641.

Teulings, C.N. (2005). Comparative advantage, relative wages & the accumulation of human capital, *Journal of Political Economy, 113*(2), 425–461. https://doi.org/10.1086/427467.

Tian, J., Coreynen, W., Matthyssens, P., & Shen, L. (2022). Platform-based servitization & business model adaptation by established manufacturers, *Technovation*, DOI: 10.1016/j.technovation.2021.102222.

Tountopoulou, M., Vlachaki, F., & Triantafillopoulou, M.-E. (2021). Universal Skills Framework for Migrants, Asylum Seekers & Refugees – A Mapping on the Required Skills While Entering the European Labour Market, *International Journal of Social Science Studies, 9*(3), 34. https://doi.org/10.11114/ijsss.v9i3.5181.

Tukker, A. (2004). Eight types of product–service system: eight ways to sustainability? Experiences from SusProNet, *Business Strategy & the Environment, 13*(4), 246–260.

Tverdostup, Maryna, & Tiiu Paas (2022). Gender Disparities in Wage Returns to Human Capital Components: How Different Are European Labour Markets? B*altic Journal of Economics, 22*(1), 28–48. https://doi.org/10.1080/1406099X.2022.2033418.

UNIDO (2004). *Foresight Methodologies*. United Nations Industrial Development Organisation, Vienna.

Vaillant, Y., Lafuente, E., Horváth, K., & Vendrell-Herrero, F. (2021). Regions on course for the Fourth Industrial Revolution: the role of a strong indigenous T-KIBS sector, *Regional Studies, 55*(10-11), 1816-1828.

Valetta, R.G. (2018). *Education, Skills, and Technical Change: implications for future US GDP growth*, Chapter Recent Flattening in the Higher Education Wage Premium: polarization, skill downgrading, or both? pp. 313–342. Chicago: University of Chicago Press.

Van Oort, F., & Thissen, M. (2021). Networked shocks & regional resilience: implications from Brexit & the Corona pandemic. Scienze Regionali. *The Italian Journal of Regional Science, 20*(1), 3-23

Vandermerwe, S., & Randa, J. (1988). Servitization of business: Adding value by adding services, *European Management Journal, 6*(4), 314-324.

Vendrell-Herrero, F., Bustinza, O.F. (2020). Servitization in Europe. In De Propris L. & Bailey D. (Eds.) *Industry 4.0 & Regional Transformations,* Routledge, London, p. 24-41.

Venturini, F. (2022). Intelligent technologies and productivity spillovers: Evidence from the Fourth Industrial Revolution, *Journal of Economic Behavior & Organization, 194*, 220-243.

Webb, M. (2020). *The impact of Artificial Intelligence on the labor market.* Available at SSRN 3482150.

WEF. (2020). The future of jobs report 2020. *World Economic Forum Report*, (October).

Winterton, J. (2009). Competence across Europe: highest common factor or lowest common denominator? *Journal of European Industrial Training, 33,* 681–700. https://doi.org/10.1108/03090590910993571.

Wosskow D. (2014). *Unlocking the Sharing Economy: an Independent Review*. Department for Business, Innovation & Skills, London. Available at https://www.gov.uk/government/publications/unlocking-the-sharing-economy-independent-review (Retrieved 16/11/2021).

Zeira, J. (1998). Workers, machines, and economic growth, *The Quarterly Journal of Economics, 113(4)*, 1091–1117.

Zhang, Q.A., & Lucey, B.M. (2017). Globalisation, the Mobility of Skilled Workers, & Economic Growth: Constructing a Novel Brain Drain/Gain Index for European Countries, *Journal of the Knowledge Economy 2017, 10*(4), 1620–1642. https://doi.org/10.1007/S13132-017-0505-X.

Zimmermann, K. F. (2005). European Labour Mobility: Challenges & Potentials. *De Economist* 2005 153:4, 153(4), 425–450. https://doi.org/10.1007/S10645-005-2660-X.

Zott, C., & Huy, Q. (2019). The affective side of dynamic capability: How founders' emotion activates human & social capital in firms, *Strategic Management Journal, 40*, 20-54.

Zwysen, W. (2021). Performance pay across Europe: drivers of the increase and the link with wage inequality. *ETUI Research Paper-Working Paper*.