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Abstract

We study the effects of digital transformation in the EU on individual employment outcomes, wage growth, and income inequality, during the decade 2010-2019. Our results allow us to formulate a "conveyor-belt" hypothesis, whereas digital skills are important for finding a job, but less so for retaining it. The ability of out-of-work individuals with higher digital skills to jump back on the labour market is reduced for those with higher education, suggesting a faster depreciation of their digital skills. A similar effect, although of limited size, is found for earning growth: out-of-work individuals with higher digital skills are not only more likely to find a job, but experience higher earning growth, compared to their peers with lower digital skills. Our results point to a vulnerability of workers "left behind" from the digital transformation and the labour market. The overall effects on inequality are, however, limited.

Keywords: Digital transformation, digital skills, inequality, employment, wages, EU

JEL Classification: J24, J31, D31

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1. Introduction

Ever since the Industrial Revolution in the XVIII and XIX centuries, technological change has been at times met with suspicion and anxiety. Fear of job displacement following periods of fast technological progress have troubled the public, researchers and policy-makers ever since. Today, people feel unease in watching computers and robots taking over tasks that were previously performed by humans. At the same time however, technological change has opened up new job opportunities, both within existing sectors and – more importantly – in sectors that did not exist before. Given enough time to adjust, labour markets have coped remarkably well, historically. However, the effects on individuals might be very different from the effects on markets. Individuals often do not have enough time to adjust to rapid changes in the labour market. Moreover, they might not be able to adjust at all, for lack of sufficient skills, lack of mobility, or other issues. The new job opportunities might be captured by different people than those who lost their old ones.

Against this background, an increasing body of research has attempted to estimate the impact of the digital transformation on the labour market. This has included research on the automation potential of digital technologies (e.g. Arntz, Gregory and Zierahn, 2016; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018) and the aggregate impact of digitalisation on the labour market, looking for instance at job polarization, labour productivity or employment (e.g. Fernández-Macías and Hurley, 2017; Graetz and Michaels, 2018; Georgieff and Hyee, 2022). The majority of contributions in the literature has focused on the industry or country level, while individual-level data has been relatively underused. However, some recent contributions do go in this direction, looking at the U.S. (Fossen and Sorgner, 2022) or individual European countries (Balsmeier and Woerter, 2019; Genz, Janser and Lehmer, 2019; Dauth et al., 2021). Most papers in this area have focused on OECD countries, with some exceptions that look at the impact of robots in emerging economies (Carbonero, Ernst and Weber, 2020) or the impact of AI on labour markets in low- and lower middle income countries (Carbonero *et al.*, 2023).

This article adds to this emerging empirical literature by quantitatively estimating the impact of the digital transformation on employment, wages, and income inequality in the 2010s, within the European Union (EU). Specifically, we make several significant contributions to this stream of literature. First, we examine the impact of digital transformation on individual employment and earnings based on three different measures of digitalisation: two indexes of digitalisation in the labour market at the level of industries, and a novel index of digital skills at the individual level. Second, we look at a large number of EU countries over a long time horizon (2010-2019), using the largest household survey data available (EU-SILC). In doing so, we offer comprehensive new evidence that contributes to the ongoing debate on the impact of the digital transformation on individuals. Third, from a methodological perspective, we use an innovative approach to overcome the limitations of the EU-SILC's four year panel rotation structure. This approach, which we refer to as “concatenated analysis”, involves repeated steps of estimation and simulation, and ultimately enables us to study individual outcomes and determinants of change for specific sub-groups of the population.

The rest of the paper proceeds as follows. Section 2 reviews the theoretical mechanisms shaping the relationship between the digital transformation and individual employment, wages and inequality, as well as existing empirical evidence. Section 3 describes our three indexes of digitalisation, the econometric methods and the concatenated analysis in detail. Section 4 presents estimates of the impact of the various measures of digitalisation on employment, earnings and inequality. Section 5 summarises and discusses the findings.

2. Theory and key findings from the literature

2.1. How does digitalization affect employment and wages?

There are various pathways through which the digital transformation may affect individual workers' employment and wage outcomes. While advancements in digital technology could lead to displacement of workers and reductions in employment and wages, it is also possible that the digital transformation is accompanied by job creation and employment and wage gains. This section describes these theoretical mechanisms in detail.

On the one hand, *displacement effects* of the digital transformation may dominate, with negative effects on employment and wages. Digitalization is advancing at an increasingly fast pace, and new technologies are becoming capable of performing a range of tasks previously undertaken by human workers (Genz, Janser and Lehmer, 2019), a process that is sometimes referred to as technological task *encroachment* (Susskind, 2017). In recent years, a significant strand of literature has attempted to estimate the automation potential of digital technologies, that is to say, the extent to which certain jobs could be replaced by technology. In a seminal contribution, Frey and Osborne (2017) estimated that in the United States, 47% of jobs are at high risk of automation (i.e. an automation risk higher than 70%). However, subsequent work stipulated that these numbers likely constitute an overestimate of the potential for automation. For instance, Arntz, Gregory and Zierahn (2016) take a task-based approach to automation potential, arguing that it is certain tasks within occupations that face a risk of replacement, rather than entire occupations as such. They estimate a much lower risk of automation in OECD countries, ranging from 6% in South Korea to 14% in Austria. Nedelkoska and Quintini (2018) carry out a similar exercise, although they expand the geographical scope of their analysis to include 32 countries. They estimate the overall share of workers at a high risk of substitution from automation to be at 14%.

Hence, the overall extent to which jobs are at high risk of automation is uncertain, as well as likely evolving over time and highly dependent on a country's institutional set-up (Merola, 2022). However, if tasks that were previously performed by labour are automatable and it becomes cheaper for technology (i.e. capital) to take over these tasks, they are expected to be automated and displaced by technology (Acemoglu and Restrepo, 2019). Where this displacement effect dominates, individual workers who are affected by labour displacing technologies should experience reduced employment stability and wage growth (Fossen and Sorgner, 2022).

The potential displacement effect, which is the focus of studies on automation potential, only showcases one side of the equation, however. This effect may be mitigated by a number of countervailing factors, as set out by Acemoglu and Restrepo (2018a, 2018b, 2019) in a series of contributions. First, digitalisation may be associated with positive *productivity effects*, leading to increases in the demand for labour in non-automated tasks, both in sectors undergoing automation and in sectors that are not affected. Productivity effects could occur through both a price-productivity and a scale-productivity effect. The former refers to technology leading to a compression in prices, which allows the industry to expand sales and take on more workers, while the latter states that lower aggregate prices may lead to an expansion in the local economy and associated spill-over effects whereby adjacent industries increase their demand for labour. In addition, increased automation may trigger capital accumulation, in turn associated with increased demand for labour. Finally, automation may increase the productivity of tasks that have already been automated (the so-called "deepening of automation"), which may be associated with increased productivity but not displacement.

Beyond these productivity effects, a significant mechanism to countervail the effects of automation is the *creation of new tasks* through digitalisation, which may lead to employment and wage gains for individual workers (Acemoglu and Restrepo, 2019; Fossen and Sorgner, 2022). New tasks could be more complex versions of existing tasks or completely new activities, potentially complementing technology (Fossen and Sorgner, 2022). Workers may have a comparative advantage relative to machines in these new tasks, directly leading to a reinstatement effect that counterbalances potential displacement (Acemoglu and Restrepo, 2018a). As such, it would be expected that digitalization is associated with increased employment and wages for workers.

On balance, then, the impact of digitalisation on workers' employment and wage outcomes is not clear-cut. If the displacement effect of technology dominates, negative effects on individual workers' employment and wages are expected (hypothesis H1a). Conversely, if countervailing mechanisms such as productivity effects and the creation of new tasks dominate, then positive effects on employment and wages are expected (hypothesis H1b). It is important to note that the labour-displacing and labour-reinstating effects of technological advances in the labour market are not mutually exclusive. At an aggregate level, it is possible that they cancel each other out (Fossen and Sorgner, 2022).

2.2. Skill-based heterogeneity in the effects of digitalization on workers

The previous section has set out how the impact of digitalization on individual labour market outcomes depends on whether labour-displacing or labour-reinstating effects of technology dominate. Yet the effect of digitalization on the labour market outcomes of individual workers is likely not uniform, but rather depends on their individual characteristics. Specifically, the effects of technological change on workers' employment and wage prospects are likely to differ by skill level, due to variance in the exposure to automation risk but also in the ability to adapt to new skill requirements.

The literature on technological change has highlighted that the potential displacement effect of technology differs by the skill level of workers, as certain types of tasks are more likely to be affected by automation. The skill-biased technological change theory (SBTC) argues that new technologies are complementary to high-skilled workers while substituting for or being neutral with respect to lower-skilled labour. This should raise relative demand for higher-skilled workers, leading to improved wage and employment prospects for these workers (Müller, 2023). At the same time, higher-skilled individuals may be better positioned to benefit from productivity effects linked to the digital transformation. Employment and wage gains from technological advancement will only be realized for individuals who can adapt to new or transformed tasks resulting from the adoption of new technologies (Fossen and Sorgner, 2022). In contrast, where a mismatch between the requirements of new technologies and the skills of the workforce arises, positive effects of digital transformation through increases in productivity and the introduction of new tasks will likely be slowed down (Acemoglu and Restrepo, 2019). Higher-skilled individuals are more likely to have skills that are complementary to technology, and may also be better prepared to deal with and adapt to new skill requirements (Fossen and Sorgner, 2022; Müller, 2023). Combined, this should lead to positive employment and wage effects of digitalisation for higher-skilled individuals, at the expense of lower-skilled workers. On the other hand, to the extent that new digital technologies such as artificial intelligence allow unskilled workers to benefit from codified competences, their productivity level might rise, an effect that might be particularly important for allowing developing countries to catch up with the global technological frontier (Ernst, Merola and Samaan, 2019; Björkegren, 2023).

A modified version of SBTC, the routine-biased technological change framework (RBTC), emphasizes that repetitive, routine tasks, which are mainly performed in medium skilled occupations, are most likely to be replaced by technology, while more complex, non-routine tasks are complementary to technology (Autor, Levy and Murnane, 2003). This implies that employment at the bottom and top of the skill distribution is likely to grow more than employment in medium-skilled occupations, where workers are most likely to be disadvantaged in terms of employment and wages, ultimately resulting in employment and wage polarization (Goos and Manning, 2007; Genz, Janser and Lehmer, 2019). Goos, Manning and Salomons (2009, 2014) pool data for 16 European countries over the period 1993-2010 and demonstrate that the RBTC phenomenon is pervasive over the period, encompassing both within- and between-industry shifts towards a reduced input of routine-intensive tasks and increased usage of non-routine analytical skills.

However, in the European context, recent scholarship provides evidence against a widespread pattern of job polarization. Fernández-Macías and Hurley (2017) develop an indicator of routine intensity, aiming to stick as accurately as possible with the theoretical definition and then run an analysis for 23 European countries over the period 1995-2007. Discordant with Goos, Manning and Salomons (2014), they do not find the phenomenon of polarisation to be pervasive. On the contrary, they observe that, while polarisation seems to be occurring for some countries, "the most frequent development was in fact one of occupational upgrading", which is more in line with the traditional SBTC hypothesis (Fernández-Macías and Hurley, 2017). In line with this result, Oesch and Piccitto (2019), looking at four European countries, find no evidence of polarization but rather – in line with SBTC – clear evidence of occupational upgrading in three countries (Germany, Spain; and Sweden), while in the UK, there is mixed evidence for job polarization and occupational upgrading depending on the measure of job quality used. In this sense, in the European context, there is only limited support for the polarization hypothesis. One explanation for this is that empirically, the expectation that occupations dominated by routine tasks are mid-skilled is not borne out in Europe. Rather; occupations involving more routine tasks tend to be lower-skilled and less complex (Fernández-Macías and Hurley, 2017; Oesch and Piccitto, 2019). Overall, we therefore expect higher-skilled workers to be more likely to benefit from digitalisation in terms of employment and wage outcomes (hypothesis H2).

Moreover, the above mechanisms, while focused on the implications of technological change for employment and wages at individual level, also have implications for aggregate inequalities in the labour market. If technology leads to increases in relative demand for skilled labour as described above, this should be associated with wage gains for skilled workers in particular. Under this scenario, the resulting increase in the wage differential between high- and low-skilled workers should result in an increase in overall wage inequality (Kristal and Cohen, 2017). Hence, we expect negative effects of digitalisation on overall wage inequality (hypothesis H3a). However, the potential inequality-increasing effect may be countervailed by other forces, such as wage-setting institutions, which may be more important than technological change in driving down or increasing inequality (Ibid.). In this scenario, digitalisation is not expected to have effects on inequality at an aggregate level (hypothesis H3b).

2.3. Differentiating between different types of technology

In practice, the effect of technology on employment and wage outcomes, and skill-based heterogeneity therein, likely depends on the type of technology examined. Much of the empirical literature has focused on the labour market effects of robots, which are likely to replace low- to medium-skilled labour, but to create fewer, higher-skilled tasks (Balsmeier and Woerter, 2019). Empirical findings tend to bear out this expectation. Graetz and Michaels (2018), looking at 17 developed economies between 1993 and 2007, find no significant effect of robots on aggregate employment, but a displacement effect for low-skilled and medium-skilled workers. Dauth et al. (2021) equally find no negative effects of robot exposure on total employment in Germany but find job losses in the manufacturing sector which were offset by gains in services. Similarly, average earnings of individual workers are hardly affected by robots, but this masks positive earnings effects for retained workers transitioning to new tasks and negative effects for those switching jobs. In this sense, skill upgrading is a significant part of the adjustment process to automation (Ibid.).

However, findings on robotics may not generalize to other types of technology. Other recent contributions to the empirical literature make use of linked employer-employee data that allows for investigating firm-level take up of technologies. Genz, Janser and Lehmer (2019) look at the use of digital tools by workers and firms' technological upgrading in Germany. They find that establishment-level investment in technology has positive effects for workers' wage development, with the most pronounced positive effects found for low- and medium-skilled workers.

Overall, these divergent results highlight the need for an integrative examination of effects of different types of technologies. Recently, several empirical contributions have made strides towards examining the joint effects of several technologies in order to provide a fuller picture of the digital transformation. Balsmeier and Woerter (2019), using Swiss data, find that increased investment in digitalization increases employment of high-skilled workers, but decreases that of low-skilled workers. However, these effects are driven by machine-based technologies (e.g. robots), while non-machine-based technologies do not have effects. For the United States, Fossen and Sorgner (2022) compare four measures of digital technology. Measures of labour-displacing technologies are associated with slower wage growth and a higher likelihood of switching employment and non-employment for individuals, while labour-reinstating technologies have positive effects on labour market outcomes, with highly educated workers the most affected by technological change. These studies illustrate the need for a nuanced understanding of the impact of technology on the labour market, which may depend not only on the characteristics of workers but also on the type of technology introduced, which may be associated with varying automation potential and impact on skill demand.

3. Data, Variables and methods

As we discussed above, the relationship between digital transformation on the one hand, and labour market outcomes on the other, is theoretically and empirically ambiguous, and depends on the time horizon considered. In this paper, we set out to quantify the overall effect of the digital transformation that took place over the decade 2010-2019 in the European Union.

Our analysis requires a dataset containing detailed, longitudinal information on personal characteristics and labour market status. The main longitudinal survey for the EU member states, and a natural candidate for our analysis, is the EU Statistics on Income and Living Conditions (EU-SILC), which is available for all the current EU Member States. The longitudinal version of EU-SILC provides employment and earnings information with detailed disaggregation by income sources, although this information refers to the previous calendar year rather than the time of the interview.[1] We restrict our analysis to the working age population (17-64 years of age, where 17 is the age an individual is first observed in the sample – i.e. the age in the initial period – and 64 is the age the individual is last observed in the sample – i.e. the age in the final period). We use three different waves of the longitudinal SILC data: 2013 (covering years 2010-2013), 2016 (2013-2016) and 2019 (2016-2019), for all EU countries with the exception of Germany.[2]

3.1. Measures of the digital transformation

We statistically match the longitudinal EU-SILC data with various measures of digital transformation, drawing on several data sources with time-variant data on digitalisation. In particular, we construct three indexes of digital intensity in the labour market. The first two indexes measure the process of digitalisation at the sectoral (macro) level and relate to the demand for labour. The third index measures digital skill at individual (micro) level and relates to the supply of labour.

Measures of digital transformation at the sectoral level

As highlighted in the previous section, the impact of digitalisation on individual labour market outcomes likely varies across different types of technologies. To account for this diversity, we construct two different sectoral-level indexes of the level of digital transformation in the labour market. The first index, which we label *digital capital intensity*, refers to intangible investments in digital technologies (software and databases). The second index (*robot density*) refers to tangible

[1] By contrast, EU-LFS has a more limited longitudinal component than EU-SILC, and income information is limited to deciles.
[2] SILC data is only available for Germany from 2018 onwards, a period too limited for our analysis.

investments, in the form of industrial and service robots. The former also covers the increasing role of machine learning algorightms, insofar as they are embedded in software or software services (e.g. online subscriptions).[3]

We construct our measure of digital capital intensity as the ratio between the stock of capital that firms have in software and databases, and the overall stock of capital excluding non-residential buildings, at the country/industry level. For this, we use data from the new integrated EUKLEMS & INTANProd database, developed by the Luiss Lab of European Economics at Luiss University in Rome, Italy (Bontadini et al., 2023). EUKLEMS & INTANProd updates the widely-used EUKLEMS productivity database and extends it with new estimates of intangible investment coherent with the INTAN-Invest framework. The dataset covers all EU countries for the period 1995-2019, and provides both measures of investment (flows) and stock of capital. We opt for looking at the capital stock, as this is less volatile and provides a better description of the extent of the ongoing digitalization process. The index is missing for Cyprus, Hungary, Ireland and Romania, and it is also missing – irrespective of the countries – for industries T (Activities of Households as Employers; Undifferentiated Goods and Services Producing Activities of Households for Own Use) and U (Activities of Extraterritorial Organisations and Bodies) in the NACE2 industry classification. Figure A1 in Appendix A shows the evoluation of the digital capital intensity index by country over time.

Second, we compute an index of robot density at the country/industry level based on the International Federation of Robotics (IFR) Industrial and Service Robots dataset (IFR, 2023).The IFR effectively collects data on installations of robotic equipment from robot manufacturers and cross-checks the result with statistics from national institutes of robotics to ensure high levels of reliability and comparability. Figures for EU Member States are generally available, although some smaller countries (Bulgaria, Cyprus, Croatia, Estonia, Latvia, Lithuania, Luxembourg, and Malta) recorded too few installations to guarantee an insightful breakdown by industry. We compute our index of robot density as the operational stock of robots per thousand employees. To derive this measure at the sectoral level, we merged the information concerning the operational stock of robots from the IFR dataset with information on the number of employees reported in the EUKLEMS & INTANProd data. The IFR's industry classification is derived and loosely organized according to the NACE Rev. 2 standard taxonomy, which is the same categorization adopted by the EUKLEMS & INTANProd. However, no exact correspondence can be found, and codes may differ, as classes that feature only minor installation counts were aggregated whereas major customer industries, such as the automotive sector, report various sub-categories. Therefore, we had to perform the appropriate aggregations to ensure that a match between the two sources could be found. Appendix A (Figure A2 and Figure A3) shows descriptive information on the evolution of the robot density index by country and industry over time.

We match the two indicators of the digital transformation to the longitudinal EU-SILC data based on the sectoral information. However, a significant methodological limitation exists, as industry information is not available in the longitudinal SILC data. We solve this challenge by statistically matching longitudinal SILC data (recipient dataset) with their cross-sectional counterpart (donor dataset), where that information is available.

The probabilistic matching is performed by comparing the donor and recipient datasets based on a sub-set of common variables, thus identifying a "best-match" for each observation in the recipient dataset. In order to reduce the number of possible matches, we use between five and eight so-called "blocking variables" which require an exact match between a recipient observation and a possible donor (i.e. the values must be identical). Three variables are consistently blocked for all countries: year of observation, year of birth, and sex. Dependent on data availability, other blocking variables may be used on top of these: region, urbanisation, education, marital status, basic activity status, 1-digit ISCO-08 occupation, employee net cash income, and employee gross cash income. When a variable is not used as a blocking variable, but is available for the country being processed, it is added into the probabilistic matching process as a "non-blocking variable" and is allowed to not match

[3] The introduction of AI is posterior to our period of investigation, but it would have been captured by our indicator – subject to the same caveats.

exactly. Non-blocking variables include living in consensual union, hours usually worked, years spent in paid work, and self-defined economic status. A score is then constructed based on the non-blocking variables to measure the similarity between each pair of longitudinal and cross-sectional observations. For each longitudinal (recipient) observation, we select the cross-sectional observation with the highest score as the donor. Industry information from the donor – together with other variables relevant for the analysis if they are missing from the longitudinal observation (as is sometimes the case for region) – are then donated to the recipient. Results of the matching are very good for all countries with the exception of Malta, with over 90% of the longitudinal observations matched to a cross-sectional donor on average, usually with a very high score. Matching rates for all countries are shown in Appendix A (Table A4). Imputation of the two demand-side indicators of digital intensity is then straightforward and involves imputing the value of the indicator for the industry in which the worker is employed (if any).

Incorporating skill-based heterogeneity

The theoretical framework highlighted that the effect of the digital transformation on individual labour market outcomes may vary by individuals' level of skills. We account for potential skill-based heterogeneity in two ways, in our analysis. First, we estimate the effects of the different measures of digitalisation separately for individuals with low, high and medium levels of education, so that heterogeneity in the effects of the measures of the digital transformation can be assessed.[4] However, while education is commonly used as a measure of skill levels in the literature (e.g. Graetz and Michaels, 2018; Dauth *et al.*, 2021), it is only a proxy measure predominantly capturing formally acquired skills, and may also mask heterogeneity in skills within educational levels (Quintini, 2011).Therefore, we incorporate a measure of individuals' actual level of digital skills in our analysis. This allows us to directly assess whether, in line with theoretical expectations, having skills that are complementary to the use of technology has positive impacts on individual labour market outcomes.

To construct our index of digital skill, we employ microdata from the Community Survey on ICT usage in households and by individuals (hereafter: ICT Survey), an annual survey conducted by Eurostat since 2002, aiming at collecting and disseminating harmonized and comparable information on the use of ICT in households and by individuals. The ICT survey contains detailed information on individual's use of technologies in a range of areas. To construct our measure of digital skills, we use 22 variables measuring different aspects of digital skills in four categories: information skills; communication skills; problem solving skills; and software skills.[5] All these variables are binary, with a value of 1 if the individual has carried out a particular task taken to be indicative of (some level of) digital skill. We use data for the years 2015-2016, 2017 and 2019, for which the full set of variables is available. This allows us to construct a time-varying index of digital skills.

We aggregate the available categorical indicators by weighting them using an item response theory (IRT) model. IRT is a methodology for aggregating a number of items in order to capture an underlying trait, in this case true digital skills, and is widely established as a method for constructing measures of skill and ability (OECD, 2016). Based on individuals' responses for each binary variable (or item) capturing digital skill, the model estimates the item's difficulty (the level of digital skills at which 50% of individuals would be expected to have performed the skill) and discrimination (a slope parameter indicating how steeply the likelihood of an individual performing this skill changes as true digital skills increase) (Demars, 2010).The implication is that the IRT model allows for estimating differentiated levels of difficulty for each aspect of digital skill, rather than simply averaging across

[4] Low education: ISCED levels 1-2; medium education: ISCED level 3; High education: ISCED levels 4-5.

[5] The variables included are (see Eurostat, 2023): Information skills – copied or moved files or folders; saved files on Internet storage space; obtained information from public authorities/services' websites; finding information about goods or services; seeking health-related information; Communication skills – sending/receiving emails; participating in social networks; telephoning/video calls over the internet; uploading self-created content to any website to be shared; Problem solving skills – transferring files between computers or other devices; installing sotware and applications; changing settings of any sofware; online puchases; selling online; using online resources; Internet banking. Software skills – Used work processing software; used spreadsheet software; used software to edit photos, videos or audio files; created presentation or documents integrating text, pictures, tables or charts; used advanced functions of spreadsheet to organise and analyse data; have written code in a programming language.

variables. The results of the IRT model are shown in Appendix A (Table A1). In a second step, we use the results of the IRT model to predict a level of digital skills for each individual in the microdata, yielding a continuous measure of digital skill.[6] Table A2 in Appendix A shows descriptive statistics on the estimated level of digital skills across various population groups. As a final step, we estimate a simple OLS regression model (Table A3 in Appendix A) predicting individual levels of digital skill based on individual characteristics (gender, age, employment status, occupation, and education) separately for each year and country.[7] The resulting estimates of levels of digital skills by population characteristics can subsequently be matched to the longitudinal microdata based on the set of common variables.

3.2. Econometric specification

We focus on estimating the impact of our measures of digital transformation on two outcomes, employment and earnings. We distinguish between gross and net earnings to investigate a potential role of welfare state policies in mitigating against the effects of the digital transformation.[8] Models are estimated for each country in isolation and for the EU as a whole.[9]

The employment model is estimated separately for the whole population, and for the sub-sample of individuals who start as employed, and follows a simple logit specification of the type:

$$e_i^{\text{end}} = Logit(e_i^{\text{start}}, x_i^{\text{start}}, d_i^{\text{start}}, \Delta D_j\ \epsilon_i) \quad (1)$$

where e_i^{end} and e_i^{start} are respectively the employment state in the final and initial period of the analysis (employed / not employed; dropped when the model is estimated on the sub-sample of individuals starting in employment), x_i^{start} are the individual characteristics in the initial period, d_i^{start} is the composite index of digital skills for individual *i* in the initial period, ΔD_j is the change between the initial and final period in the indexes of demand of digital skills (only included when estimating the model on the sub-sample of individuals employed in the base year, for which industry information is available), and ϵ_i is a random disturbance. The start and end period vary depending on the sample being used – see Section 3.3 below).

Note the two different indexes of digital skills involved: d_i is the individual-level measure of digital skills described above. D_j on the other hand is a sectoral-level measure of digitalisation (digital capital intensity and robot density), computed on data aggregated at the industry level. It is an attribute of the industry, not of the individual: as such, two individuals employed in the same industry – but with different occupations - will have the same value of ΔD_j. Moreover, the indicator is not defined for individuals who are not employed, which prevents us from using it when including this sub-group of the population in the estimation sample.

Note also that controlling for a heterogenous level of digital skills d_i is crucial in the analysis, as we can expect the supply of digital skills to correlate with other individual characteristics such as age and education.

As for what concerns time variation of the indexes of digital skills, two things have to be noted:

[6] The measure is standardized to mean 2 and standard deviation 1, following OECD (2016).
[7] Given that the indicators in the ICT Survey only cover the years 2015, 2016, 2017 and 2019, we impute the indicator to the years non covered by estimating a linear time trend – hence assuming that the trend in digital skills between 2010 and 2014 is the same as between 2015 and 2019.
[8] We use total gross household income (variable HY010) for gross earnings, and total disposable household income (variable HY020) for net earnings. Total gross household income (HY010) is computed as the sum for all household members of gross personal income components plus gross income components at household level. disposable household income (HY020) is gross income minus taxes plus benefits. Values are yearly.
[9] With the exception of Germany, as explained above.

- d_i only enters in the initial period of the analysis. This is because we cannot rule out that the evolution of individual skills depends on individual employment outcomes. This reverse causation introduces endogeneity and strongly suggests removing measures of individual digital skills at later periods from the specification.

- D_j enters both in the initial and in the final period, to capture changes in labour demand.

In addition to the employment state (e_i^{start}), the individual characteristics (x_i^{start}) that we control for in the analyis of employment transitions, all measured in the base year, are: age (2nd polynomial), sex, education (three levels), region (NUTS-2), degree of urbanisation (for most countries: urban, rural and mixed), occupation (ISCO-08 1-digit classification, only for those starting in employment), and gross earnings quintiles.[10] As mentioned above, to account for heterogeneity in the effects of the digital transformation, we also introduce interaction terms between our three indicators of digital transformation and education.

Gross and net earnings are then (separately) modelled following a linear specification where the outcome variable is the percentage change in earnings, Δy_i.[11] We use the same covariates of the employment models, but also control for the employment state in the final year, e^{end}:

$$\Delta y_i \;=\; b_0 + b_1 e^{start} + b_2 e^{end} + b_3\, x_i^{\text{start}} + b_4\, d_i^{\text{start}} + b_5\, \Delta D_j +\; b_6 I_i, \epsilon_i) \qquad (2)$$

where I stands for the interaction terms (same as above). Accordingly, in the analysis we first simulate employment outcomes, and then earnings conditional on employment outcomes.

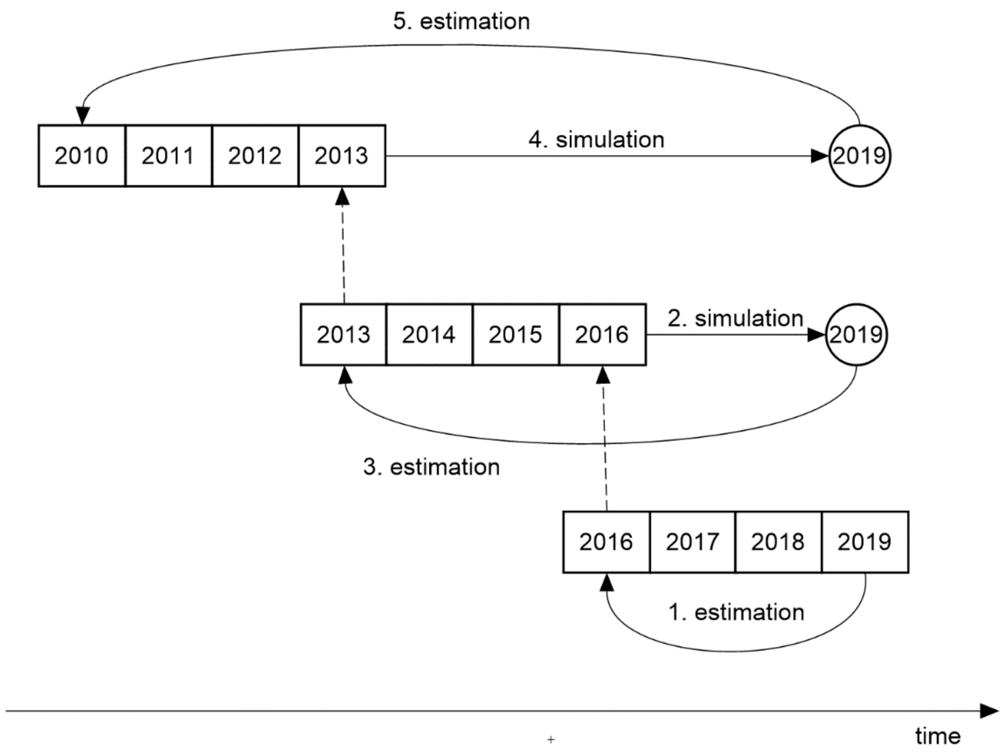
The earning model is estimated separately for those observed as employed in the initial year, and for those observed as not employed. For the not employed, just as for the employment model described above, we exclude the indicators of demand of digital skills, as industry information is not available for this group.

3.3. Concatenated analysis

The rotational panel structure of EU-SILC is limited to 4 years. To address the limited longitudinal dimension of EU-SILC, we perform a concatenated analysis where labour market outcomes are simulated over a 10-year horizon based on the econometric results for shorter periods. More specifically, we exploit the overlapping nature of EU-SILC data, where in each wave there are individuals that are also included in previous waves. Figure 1 describes the iterative estimation-simulation procedure.

[10] The degree of urbanisation is dropped from the specification for the Netherlands and Slovenia, as the variable is missing for those countries.
[11] More precisely, we approximate the percentage change in earnings with the logarithmic difference, then approximate logarithms with the inverse hyperbolic sine transformation to avoid the problem that logarithms are not defined at 0 (the inverse hyperbolic sine of 0 is 0). Hence, our outcome variable is also defined when earnings in the initial period are 0 – in this case its value is simply the inverse hyperbolic since of earnings in the final period.

Figure 1: Concatenated analysis



Labour market outcomes are estimated using the 2016-2019 longitudinal wave, based on individual characteristics measured in 2016. The relationship between 2016 inputs and 2019 outputs is then exploited to simulate 2019 outputs for the 2013-2016 wave. Predicted labour market outcomes in 2019 are then related to observed inputs in 2013, using the 2013-2016 wave of data. The relationship between 2013 inputs and 2019 (predicted) outputs is then exploited to simulate 2019 outputs for the 2010-2013 wave. This allows us to finally relate 2010 inputs to 2019 (predicted) outcomes.[12]

The concatenated analysis therefore involves the following steps:

1. Estimation of 2019 outcomes (employment and earnings) on 2016-2019 wave.

2. Simulation of 2019 outcomes on 2013-2016 wave, based on the results of Step 1.

3. Estimation of 2019 (projected) outcomes on 2013-2016 wave.

4. Prediction of 2019 outcomes on 2010-2013 wave, based on the results of Step 3.

5. Estimation of 2019 (projected) outcomes on 2010-2013 wave.

Only the observations present in all 4 years of each wave are kept for the analysis; the number of observations retained varies from country-to-country but is around one-quarter of the total number of observations.[13] Appendix B reports the sample for each country and provides descriptive statistics for our estimation sample.

[12] We also run analyses on each sub-period (2010-13, 2013-16 and 2016-19) separately. The analyses on the sub-periods do not require simulation, and are therefore safe from a possible source of error/noise. Results on the sub-periods (available on request) broadly confirm the general pattern emerging from the concatenated analysis.

[13] In order to increase sample size, we could include observations with only two or three years of presence in the data, but this would require increasing the number of steps in the concatenated analysis, with dubious effects on the quality of the results.

Prediction of employment outcomes from the logit models produces individual *probabilities* of being employed. These are then turned into predictions about employment outcomes by means of a Montecarlo simulation.[14] As this procedure involves stochastic events (the random draws of the Montecarlo simulation), we repeat it 100 times when estimating the models on the pooled EU-wide dataset, and 25 times for each country in the country-specific models. We then compute point estimates as averages of the point estimates obtained in each run, while bootstrapped confidence intervals are computed based on the variability of the point estimates in each run.

As an illustration of the process, Appendix C discusses each step in detail with reference to the pooled EU sample, providing estimation results and validation statistics for *one* random Montecarlo draw. Results based on 100 Montecarlo replications are presented in the next Section.

4. Results

4.1. Effects on employment

Our first set of results concerns the effects of the digital transformation on employment, by levels of education. We first discuss results of the effects of two measures of digitalization at the sectoral level, digital capital intensity and robot density, on employment. As described previously, the effects of (changes in) these indicators can be measured, at an individual level, only for those who start as employed, and for whom industry affiliation is therefore defined. The sample is therefore restricted to individuals who are employed in the base year. Table 1 shows the estimated mean, standard deviation, minimum and maximum for the coefficients for the two sectoral-level measures of digitalisation, as computed on the 100 Montecarlo repetitions of the concatenated analysis on the pooled EU sample. For ease of interpretation, the coefficients are expressed in odds ratio: they therefore measure the increase in the odds of being employed in 2019 corresponding to a one standard deviation increase in the value of the index in 2010. Values above 1 indicate a positive effect of digital skills, while values below 1 indicate a negative effect.

None of the effects are statistically significant, meaning that we find no evidence of either negative (hypothesis H1a) or positive (H1b) effects of the digital transformation on individual employment outcomes. In other words, individuals who have a job seem to be, on average, insulated from the effects of digitalization, in terms of the probability of remaining in employment. In addition, contrary to hypothesis H2, there is no indication of skill-based heterogeneity in the effects of the digital transformation on employment, when measuring skills in terms of the level of formal education. When running the models separately for each country, in accordance with the EU-level analysis, results are rarely significant. Industry-level changes in the level of digitalisation do not appear to affect insiders (i.e. those already in work) much, in terms of their likelihood to remain in employment.[15]

We next present the results for our individual-level measure of digital skills. Table 2 reports the mean, standard deviation, minimum and maximum for the coefficients for the digital skills index, as computed on the 100 Montecarlo repetitions, separately for the whole EU sample and for those who start as employed in 2010. Again, coefficients are expressed in odds ratio, measuring the increase in the odds of being employed in 2019 corresponding to a one standard deviation increase in the value

[14] This involves drawing a random number from a uniform distribution between 0 and 1, and comparing it with the estimated probability. A positive outcome (in our case, employment) is then assigned if the random number is below the predicted probability – this happens exactly with the predicted probability.

[15] Although it is possible that these individuals change job / industry, something we cannot check in our data. Details of the country-specific analysis are available on request.

of the index in 2010. Values above 1 indicate a positive effect of digital skills, while values below 1 indicate a negative effect.

Table 1 - Estimated odds ratio for the effects of changes in digital capital intensity and robot density in the industry of employment in 2010 on 2019 employment status. Sample: EU27 (excluding Germany)

	Digital capital intensity			**Robot density**		
Sample		Employed			Employed	
Education	Low	medium	high	low	medium	high
Mean effect	1.031	1.069	1.075	1.004	1.000	0.998
Std.dev.	0.127	0.084	0.126	0.008	0.003	0.006
Min	0.853	0.880	0.861	0.984	0.994	0.990
Max	1.405	1.286	1.549	1.022	1.005	1.024

Note: The table reports summary statistics for the estimated coefficients from Step 5 over 100 repetitions of the concatenated analysis. The coefficients measure the increase in the odds of being employed in 2019 corresponding to a one standard deviation increase in the value of the index between 2010 and 2019 (an odds ratio of 1 indicating no effects).

Source: Our computation on longitudinal EU-SILC data 2010-2019.

Table 2: Estimated coefficients for the effects of the 2010 endowment of digital skills on 2019 employment status. Sample: EU27 (excluding Germany).

Sample	All			employed		
Education	low	medium	high	low	medium	high
Mean effect	1.443	1.447	1.221	1.003	1.190	0.984
Std.dev.	0.091	0.088	0.128	0.219	0.247	0.209
Min	1.300	1.264	0.931	0.469	0.593	0.524
Max	1.743	1.666	1.531	1.959	2.033	1.463

Note: The table reports summary statistics for the estimated coefficients from Step 5 over 100 repetitions of the concatenated analysis. The coefficients measure the increase in the odds of being employed in 2019 corresponding to a one standard deviation increase in the value of the index between 2010 and 2019 (an odds ratio of 1 indicating no effects).

Source: Our computation on longitudinal EU-SILC data 2010-2019.

The coefficients for the overall population are strongly positive, especially for individuals with a low and medium level of education. In contrast, they are not significant on average in the sample of individuals initially observed as employed. This suggests that the effect of digital skills is particularly strong for those who start not in work.[16] The country-specific analysis confirms that this pattern is of

[16] The overall effect (estimated) being a weighted average of the effect for the employed (estimated), and the effect for the not employed (not estimated). The reason for not estimating the model separately on the sub-sample of non-employed individuals in 2010 is the smaller sample size of this group, which is problematic in the context of our non-linear specification for employment outcomes. Results for the not employed are therefore inferred by comparing results for the whole population and results for the employed.

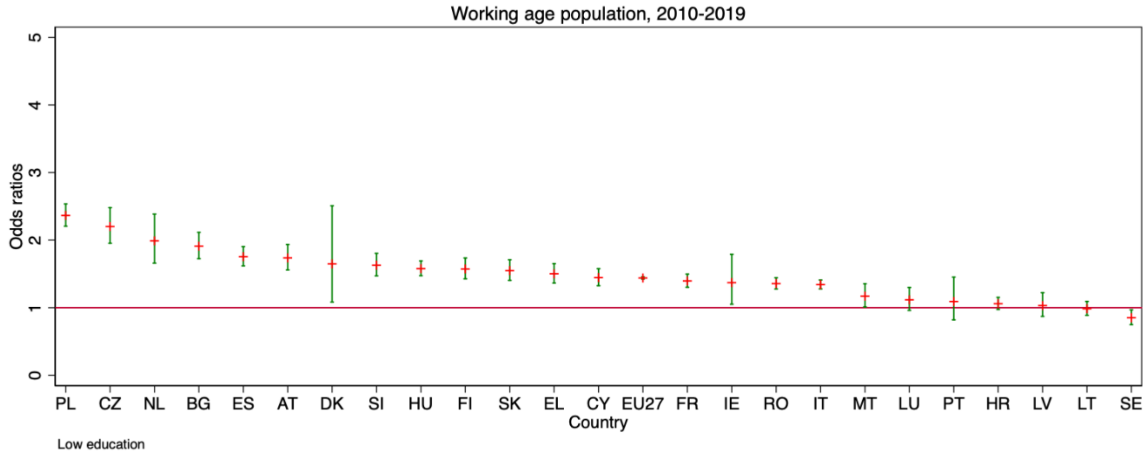
general validity throughout the EU. We find that, for most countries and in the samples including all working age individuals, digital skills endowment in 2010 increases the probability of being employed in 2019 (Figure 2). There is some heterogeneity across EU countries in terms of the magnitude of this effect, but the effect is consistently positive. As in the EU-wide analysis, the effect is strong especially for individuals with low or medium education. However, when we reduce the sample to those who were in employment in 2010, the effect disappears. Consistent with the EU-level analysis, the effect is therefore stronger for those not in employment.

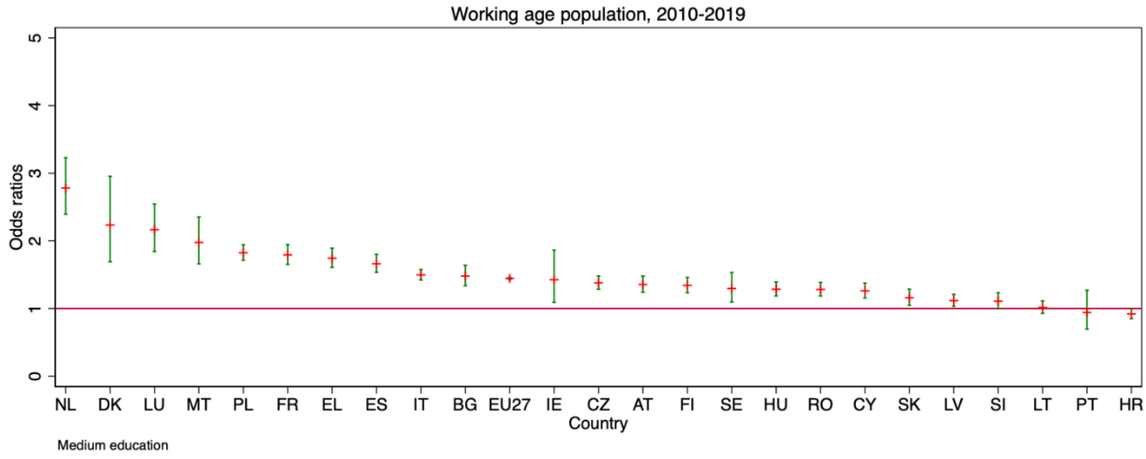
The Montecarlo analysis hence shows that digital skills are important to find a job, yet less so to retain it. The results provide some evidence in support of hypothesis H2 and the broader theoretical expectations associated with SBTC: individuals with higher levels of digital skills – i.e. a type of skill that is by design complementary to technology - appear to be advantaged in terms of employment outcomes. It should also be stressed that the effect of digital skills is observed even while holding constant individuals' level of education. This highlights the fact, as discussed previously, that the level of education does not capture hetereogeneity in (digital) skills to a sufficient extent. The fact that the positive effect of digital skills is reduced for individuals with high education may reflect the high average level of digital skills of this group (see Appendix B, Tables B2-B4), which could imply that having digital skills is less significant as a differentiating factor between individuals. Furthermore, their more advanced skills might experience a faster depreciation, given that highly-educated individuals tend to have more specialized, task-specific human capital (Fossen and Sorgner, 2022).

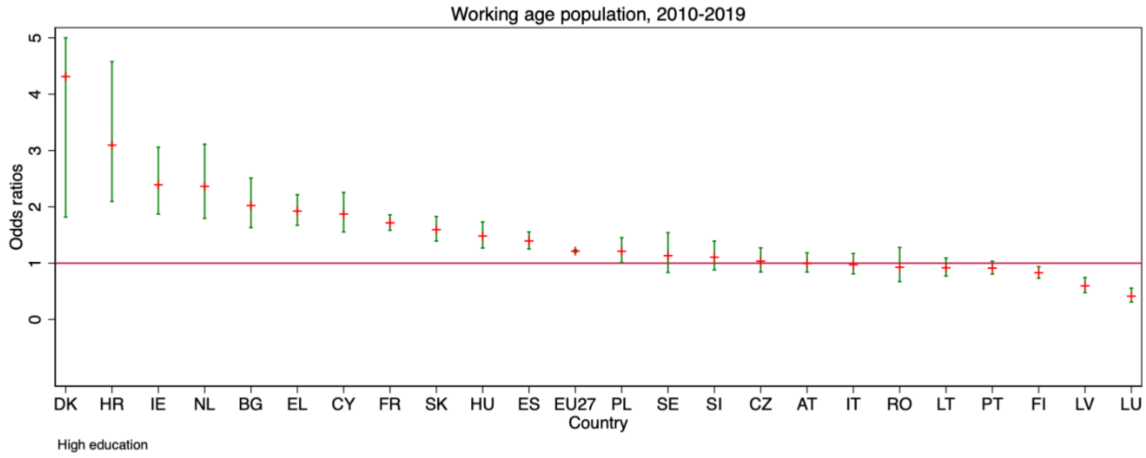
Our analysis of the effects of digital transformation on EU economies over the period 2010-2019 finds that digital skills positively impacted employability (probability to find a job for those not in employment), especially for individuals with low and medium education. This result is consistent with a "conveyor belt hypothesis". Work is the conveyor belt that accompanies individuals through change, the digital transformation in our case. Those in work adapt and evolve, together with the labour market. Those out of work can hope to jump on the conveyor belt, and their chances of doing so are related to their level of digital skills, among other things. This is an hypothesis that we advance based on our empirical results, but that would need more testing, ideally exploiting linked employer-employee administrative datasets.

If confirmed, our results point both to an overall strength of the EU labour markets, given the increase in digital skills observed during the period, and to individual vulnerabilities. The other side of the coin, in fact, is that individuals who have missed the digital transformation and have therefore accumulated lower digital skills have been put at a disadvantage.

Figure 2 – Effects of digital skills endowment in 2010 on the probability of being employed in 2019 (odds ratio) by education attainment level, all individuals aged 17-55 in 2010







Note: EU27 is excluding DE. The figures report box-plots for the estimated coefficients from Step 5 over 25 repetitions of the concatenated analysis (100 repetitions for the EU27). The coefficients measure the increase in the odds of being employed in 2019 corresponding to a one standard deviation increase in the value of the index. The sample is restricted to 55 years old in 2010 as these individuals would be 64 years old in 2019.

Source: Our computation on longitudinal EU-SILC data 2010-2019.

4.2. Effects on earnings

Our second set of results concerns the effects of the digital transformation on gross and net earnings.

As for employment outcomes, the effects of digital capital intensity and robot density on earnings can be measured only for those in employment, as they refer to changes happening at the level of the industry each worker was initially observed in. Table 3 shows the estimated coefficients of digital capital intensity and robot density for the model estimated on the EU-wide sample. The effects are generally small. Some slightly larger and positive effects can be detected only for the effects of digital capital intensity in the low education sample. They however point to a 2% *ceteris paribus* increase in gross earnings over a 10 year period, still a small effect corresponding to a rather large (one standard deviation) variation of the index. The country-level effects are generally small, and consistent with the limited effects identified at the EU-wide level.[17] Hence, as in the case of employment, we do not find evidence of either a negative (hypothesis H1a) or positive (H1b) effect of various types of digitalisation at sectoral level on individual earnings outcomes, for both net and gross earnings.

Table 3 - Estimated coefficients for the effects of changes in digital capital intensity and robot density in the industry of employment in 2010 on (approximate) gross earnings growth between 2010 and 2019. Sample: EU27 (excluding Germany).

	Digital capital intensity			**Robot density**		
Sample		employed			Employed	
Education	low	medium	high	low	medium	high
Mean effect	0.019	-0.001	-0.006	-0.0016	-0.0002	0.0002
Std.dev.	0.001	0.000	0.000	0.0000	0.0000	0.0000
Min	0.018	-0.002	-0.006	-0.0017	-0.0003	0.0001
Max	0.021	0.000	-0.005	-0.0015	-0.0002	0.0002

Note: The table reports summary statistics for the estimated coefficients from Step 5 over 100 repetitions of the concatenated analysis. The coefficients measure the approximate percentage change in gross yearly earnings (difference in inverse hyperbolic sine transformation) between 2010 and 2019 corresponding to a one standard deviation increase in the value of the index over the same period.

Source: Our computation on longitudinal EU-SILC data 2010-2019.

Table 4 shows the estimated coefficients for the effects of digital skills on gross earnings. We find a positive impact on gross earnings growth for those not in employment in the base year, but a negative effect for those in employment, although these effects are again rather small. The positive effect (for those not in employment) fades away with high education, while the negative effect (for those in employment) is stronger for low education. For the low educated, a (rather large) increase in digital skills by one standard deviation brings an increase in gross earnings over a 10-year period of only 2% if starting as not employed, and a similar decrease if starting as employed (Table 4).

[17] Details of the country-specific analysis are available on request.

Table 4 – Estimated coefficients for the effects of the 2010 endowment of digital skills on gross earnings growth between 2010 and 2019. Sample: EU27 (excluding Germany).

Sample	Not employed			employed		
Education	Low	medium	high	Low	medium	high
Mean effect	0.019	0.024	0.003	-0.017	-0.007	-0.009
Std.dev.	0.001	0.001	0.001	0.001	0.001	0.001
Min	0.016	0.022	0.001	-0.020	-0.010	-0.012
Max	0.022	0.028	0.007	-0.012	-0.004	-0.007

Note: The table reports summary statistics for the estimated coefficients from Step 5 over 100 repetitions of the concatenated analysis. The coefficients measure the approximate percentage change in gross yearly earnings (difference in inverse hyperbolic sine transformation) between 2010 and 2019 corresponding to a one standard deviation increase in the value of the index.

Source: Our computation on longitudinal EU-SILC data 2010-2019.

Hence, on the one hand, in alignment with the results for employment outcomes and hypothesis H2, individuals who are not in employment appear to benefit from having a higher level of skills. This is consistent with SBTC: having skills that are complementary to the digital transformation is associated with superior labour market outcomes. Note that the positive effect of digital skills for those not in employment is a *ceteris paribus* effect that controls for the end-of-period (i.e. 2019) employment state, so it is not the case that those not in employment with higher digital skills experience higher earnings growth *because* they are more likely to find a job: rather, it is that these people, *in addition* to having a higher probability to find a job, end up in better paying jobs (with respect to similar individuals who also started out of job, found a job, but have less digital skills). Similarly to what we found with the probability of being in employment at the end of the period, the fact that the effect fades away for the not employed with high education points to a higher depreciation of more advanced digital skills. On the other hand, for individuals who are already in employment, (small) negative effects of digital skills on gross earnings growth are observed, especially for individuals with low education. One potential interpretation is that low-educated individuals with higher digital skills tend to work in jobs that are more structurally vulnerable to automation, or less protected (e.g. less unionised). Among those employed, the stronger negative effect of digital skills for the low-educated suggests that this group suffers more from digital transformation. However, given the overall low magnitude of the effects, these results should be interpreted cautiously.

The effects for gross and net earnings not only go in the same direction, but are of comparable size (see Appendix D for the results on net earnings). This points to a limited role of policies, likely to be attributed to the small effects of digital transformation on earnings documented above.

The country-level analysis shows a mixed picture, with no consistent pattern emerging. This is in line with the small size of the effects also documented in the pooled EU sample: country-specific estimates are rarely beyond plus or minus 10% for a large increase in digital skills (one standard deviation) over a long period (10 years). Given the small size of the effect, we caution against over-interpreting country differences. However, our country-specific results point to a larger number of countries where the estimated effects of digital skills on changes in gross earnings are positive rather than negative, for the sample of individuals not employed in 2010. Conversely, we find the opposite for the sample of those who are employed in 2010. This pattern is consistent with the results using the pooled sample.[18]

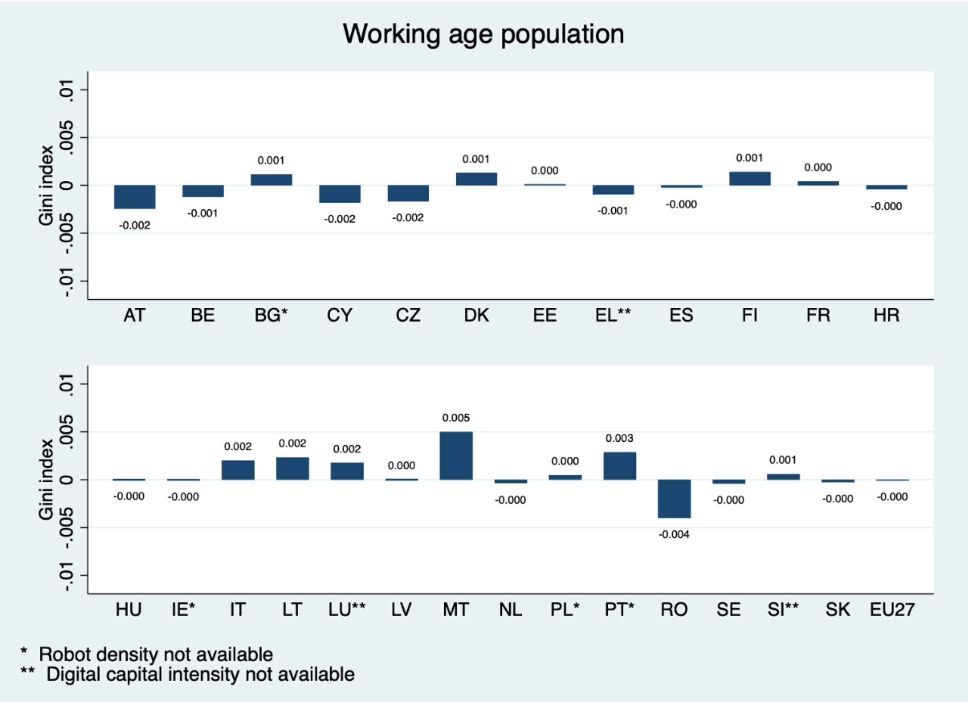
[18] Details of the country-specific analysis are available on request.

4.3. Effects on inequality

To evaluate the effects on inequality, we recur to a simple counterfactual exercise where the sectoral-level indexes of digital transformation are kept constant at their 2010 level, and digital skills on the supply side are de-trended to mimick the loss of one decade of skills growth. We then compare the value associated with the baseline (observed values of the indexes of digital transformation) and the counterfactual (modified values). The baseline is therefore "with digital transformation active", while the counterfactual is "with digital transformation paused". Differences between the baseline and the counterfactual hence identify the estimated effect of a decade of digital transformation.

Figure 3 displays the results for gross earnings inequality, in terms of the difference between the Gini coefficient in the baseline, and that in the counterfactual. A similar exercise shows negligible effects on net earnings inequality and poverty. Hence, we find no evidence that digital transformation has negative impacts on inequality (hence supporting hypothesis H3ab against H3a). However, the quantitative exercise shown here cannot speak to whether labour market and social policy institutions – such as wage setting mechanisms – played a role in limiting the potential effects of the digital transformation on inequality.

Figure 3 - Impact of digital transformation on gross income inequality (Gini coefficient), 2010-2019



Source: Our computation on longitudinal EU-SILC data 2010-2019.

5. Discussion

Apart from the effects on employment, which have suggested our "conveyor belt hypothesis", little other effects are found. Direct effects of digital skills on gross earnings (beyond the effects already vehiculated by education and occupation) are positive for individuals who start out not in employment and negative for those employed in the base year, but in both cases, these effects are substantially very small in size. Indicators of digital transformation on the demand side have also little bearing on individual outcomes. Finally, no effects of digital transformation on inequality can be detected, according to our estimates.

There are several possible explanations for the overall limited effects found, in light of the ongoing concerns related to the digital revolution. First, our study uses nationally representative samples. The fact that, for the most part, we do not observe impacts of the digital transformation on employment and earnings does not imply that digitalisation has no effects on labour markets. Rather, as highlighted in the review of theory, the effects of digitalisation may go in different directions and could thus cancel each other out at an aggregate level. This neutralizing effect, which posits that potential displacement effects[19] of the digital transformation may be offset by countervailing mechanisms such as productivity effects[20] or the creation of new tasks[21], is prominently discussed in the literature (e.g. Acemoglu and Restrepo, 2019; Fossen and Sorgner, 2022) and serves as a plausible explanation of our results, especially when adopting a level of inquiry at the national level, as is done in this study. Moreover, the literature on robotics also points to a limited impact on employment and earnings in Europe, though these aggregate effects may hide differences across specific sectors or population groups (Graetz and Michaels, 2018; Dauth et al., 2021). Based on our research design and data, we have no information, and also no statistical power, to analyse what happens at lower zoom levels than the national one, and the data we use does not contain information on individual firms/plants, making it impossible to reconstruct trajectories following specific technological upgrades. Relatedly, a second explanation concerns the time horizon of the analysis, which extends over a full decade. During a longer period of time, affected individuals have the opportunity to move to other jobs, in other firms, occupations, sectors, areas. Our results might therefore point to an aggregate resilience of EU economies, compatible with localised and temporaneous adverse effects. Indeed, at national level and considered over longer periods of time, our findings suggest that negative effects of the digital transformation may be more attenuated than anticipated, pointing to the adaptive and resilient nature of labour markets in the long-run.

A third explanation is that the degree and nature of the digital shock experienced during the 2010s in the EU was perhaps less pronounced than in other contexts (e.g. specific sectors in the U.S.) or time periods (e.g.1990 – 2010). This period has experienced relatively stable advancements in existing digital technologies, as opposed to the emergence of new paradigms that dramatically disrupted labour markets. For instance, advancements in cloud computing, big data analytics and the mobile internet, significant digital developments of the decade, were largely evolutions from earlier technologies rather than revolutionary changes. Moreover, while these innovations had profound impacts on businesses – streamlining of operations and reduction of costs (cloud computing), shift in consumer behaviour and business models (mobile internet), data-driven decision-making (big data analytics) – they did not always carry with them direct employment effects, often times resulting in job evolution and the creation of new opportunities rather than large-scale labour disruptions. Relatedly, adopting a temporal perspective, one could posit that earlier periods, such as 1990 – 2010, witnessed significant innovations and foundational shifts in technology that more directly transformed labour markets. The internet revolution fundamentally transformed how industries operated, with profound effects across economies, including indirect effects (cheaper communication and connectivity) that could be aruged to have further increased globalisation and outsourcing. This

[19] Displacement effects refer to the ability of new technologies to perform tasks previously undertaken by humans, implying that certain jobs could be replaced by technology.

[20] Productivity effects refer to increases in the demand for labour in non-automated tasks, both in sectors undergoing automation and in sectors that are not affected. Productivity effects could occur through both a price-productivity and a scale-productivity effect. The former refers to technology leading to a compression in prices, which allows the industry to expand sales and take on more workers, while the latter states that lower aggregate prices may lead to an expansion in the local economy and associated spill-over effects whereby adjacent industries increase their demand for labour.

[21] The creation of new tasks through digitalisation may lead to employment and wage gains for individual workers. New tasks could be more complex versions of existing tasks or completely new activities, potentially complementing technology. Workers may have a comparative advantage relative to machines in these new tasks, directly leading to a reinstatement effect that counterbalances potential displacement.

in contrast to the 2010s, where advancements were more about deepening and extending the impact of earlier innovations.

Furthermore, it is important to note that our study provides very limited bearings on the effects of A.I. and the impending new wave of transformation. This is largely because, during the 2010s, despite significant speculation about the potential impact of A.I., its real-world implementation across various industries remained tentative and experimental. However, with the recent rapid expansion of applied A.I. in various sectors – including large language models, autonomous vehicles, and advanced intelligent robotics – the 2020s may present a different scenario. Nevertheless, it will remain important to not let rhetoric dominate over reason, since it is interesting to note that the narrative around the digital revolution might have run faster than reality in the 2010s. While early signs may suggest the opposite, this could also possibly hold true for the next stage of the digital revolution.

Fourth, it is important to note that our approach has certain limitations which might also explain the limited results found. Measuring digital transformation over time proves difficult, and our indexes might miss important aspects of the phenomenon. Moreover, adoption by domestic firms of the new production processes might reduce the pressure from international competition, hence preserving jobs. Finally, and on a more technical note, probabilistic imputation of the indexes of digital transformation introduces noise in the estimates, which is further increased by our concatenated analysis (although results for the sub-periods, not involving simulations, broadly confirm the picture depicted here). Both steps are required to overcome the limitations of the data, but there are limits to what they can achieve. Better data – specifically in the form of a longer longitudinal component of the SILC and inclusion of additional variables on work characteristics and human capital – would be a welcomed development.

While, for the reasons discussed above, our analysis largely indicates a relatively modest impact of the digital transformation on the labor market during the 2010s, the results do suggest an important finding: digital skills are crucial to finding a job, yet less so to retain one. What we term the "conveyor belt hypothesis" stipulates that those in employment (on the belt) will be accompanied in better navigating the digital transformation, acquiring necessary skills while on the job. However, for individuals out of a job, and especially for ones with low and medium levels of education, digital skills significantly impact their employability. In other words, those unemployed risk not making the jump onto the conveyor belt and being left behind. From a policy perspective, this underscores the importance of up- and re-skilling initiatives, especially for older generations. While younger cohorts tend to enter the labour market with higher levels of digital skills, older individuals who are or become unemployed often have less developed digital literacy and are at a disadvantage[22]. As such, adult learning is an important consideration in this context. Effective life-long learning opportunities that equip adults with digital skills are a key policy lever to enable them to better participate in the labour market. Such ambitions are reflected in the European Pillar of Social Rights Action Plan, which aim for at least 60% of adult participation in annual training by 2030. While progress is being made – 43.7% in 2016 to 46.6% in 2022[23] – more will be required to reach this important policy objective and thereby help mitigate further increases in job displacement, poverty and income inequality that may arise from future digital develpoments.

[22] Individuals with basic or above basic overall digital skills by age cohort, EU-27 (Eurostat, 2023 - isoc_sk_dskl_i21):
16 – 24-year-olds: 70%
25 – 34-year-olds: 70%
35 – 44-year-olds: 65%
45 – 54-year-olds: 57%
55 – 64-year-olds: 44%
65 – 74-year-olds: 28%

[23] Eurostat: Participation rate in education and training by sex (trng_aes_100) https://ec.europa.eu/eurostat/databrowser/view/trng_aes_100/default/table?lang=en&category=educ.educ_part.trng.trng_aes_12m.trng_aes_12m0

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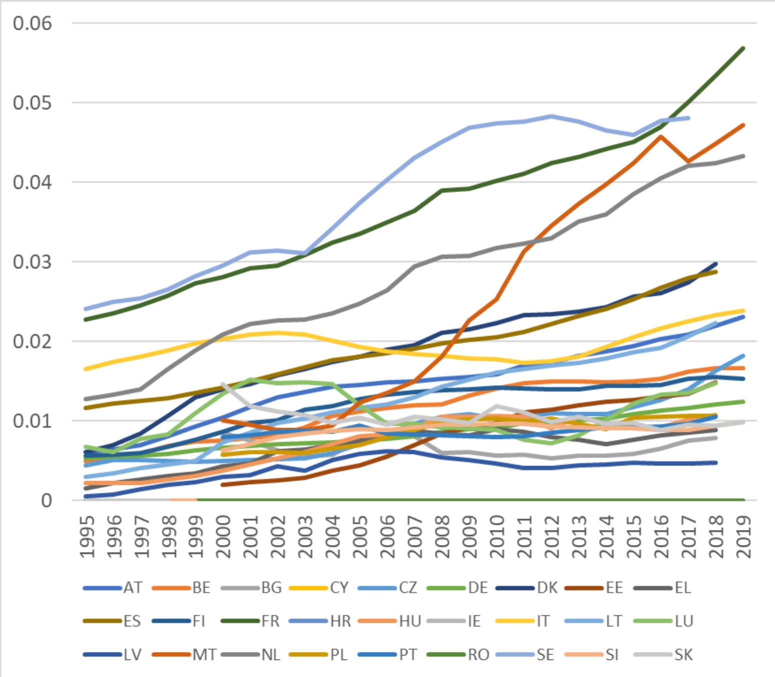
Appendixes

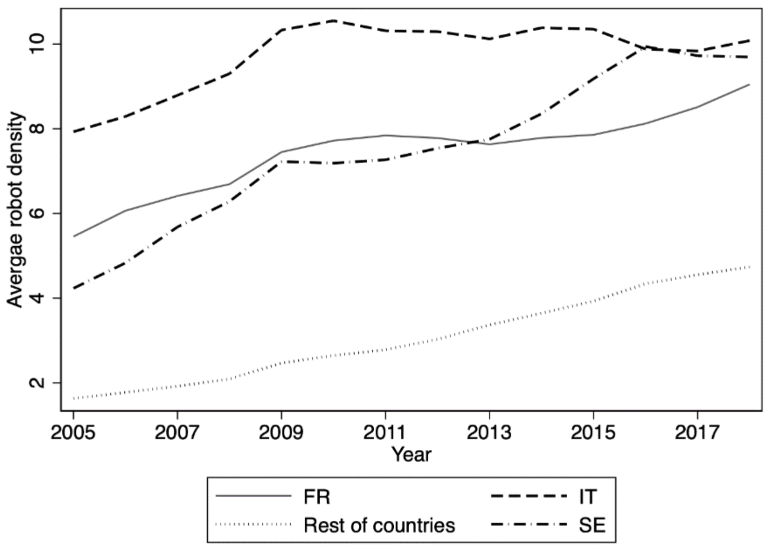
Appendix A. Modelling results and descriptive statistics for the measures of digital transformation

Figure A1: Digital capital intensity by country, 1995-2019



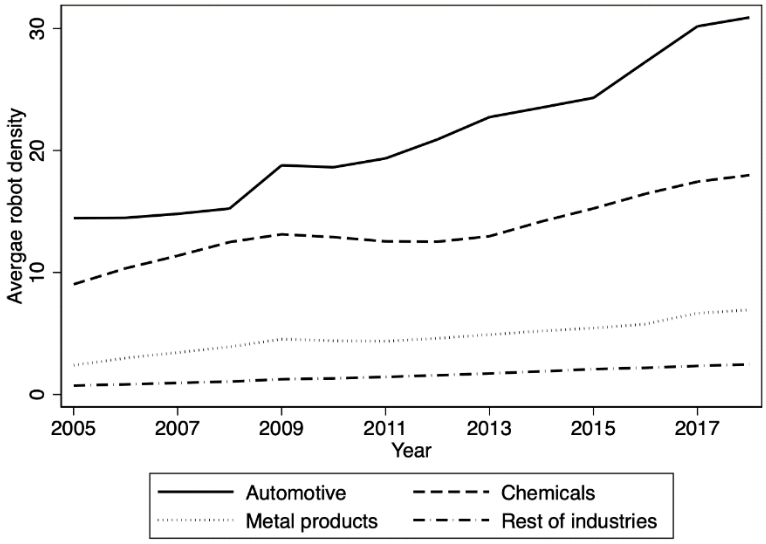
Note: Authors' elaboration based on data from Bontadini et al. (2023)

Figure A2: Average robot density by country, 2005-2019



Note: Authors' elaboration based on data from IFR (2023), EU excluding Germany

Figure A3: Average robot density by industry, 2005-2019



Note: Authors' elaboration based on data from IFR (2023), EU excluding Germany

Table A1: Results of the Item Response Theory Model To Predict Levels of Digital Skill

Variables		Coeff.	Std. err.	P>|z|	Conf. int.	
Copied or moved files into a folder						
	Discrimination	3.51	0.03	0.00	3.45	3.56
	Difficulty	-0.59	0.00	0.00	-0.60	-0.58
Saved files on Internet storage space						
	Discrimination	1.23	0.01	0.00	1.21	1.24
	Difficulty	0.83	0.01	0.00	0.82	0.85
Obtained information from public authorities/services' websites						
	Discrimination	1.05	0.01	0.00	1.03	1.07
	Difficulty	-0.11	0.01	0.00	-0.12	-0.10
Finding information about goods or services;						
	Discrimination	1.15	0.01	0.00	1.14	1.17
	Difficulty	-1.45	0.01	0.00	-1.47	-1.43
Seeking health-related information.						
	Discrimination	0.64	0.01	0.00	0.63	0.65
	Difficulty	-0.68	0.01	0.00	-0.70	-0.66
Sending/receiving emails						
	Discrimination	1.80	0.02	0.00	1.77	1.83
	Difficulty	-1.56	0.01	0.00	-1.58	-1.55
Participating in social networks						
	Discrimination	0.73	0.01	0.00	0.72	0.75
	Difficulty	-0.59	0.01	0.00	-0.61	-0.58
Telephoning/video calls over the internet						
	Discrimination	0.64	0.01	0.00	0.63	0.66
	Difficulty	0.47	0.01	0.00	0.45	0.49
Uploading self-created content to any website to be shared						
	Discrimination	0.86	0.01	0.00	0.84	0.87
	Difficulty	0.97	0.01	0.00	0.95	0.98
Transferring files between computers or other devices						
	Discrimination	2.62	0.02	0.00	2.59	2.65
	Difficulty	-0.53	0.00	0.00	-0.53	-0.52
Installing software and applications (apps)						
	Discrimination	2.39	0.01	0.00	2.36	2.42
	Difficulty	-0.25	0.00	0.00	-0.26	-0.24
Changing settings of any software						
	Discrimination	2.02	0.01	0.00	2.00	2.05
	Difficulty	0.55	0.00	0.00	0.54	0.56
Online purchases (in the last 12 months)						
	Discrimination	1.18	0.01	0.00	1.17	1.20
	Difficulty	-0.29	0.01	0.00	-0.30	-0.28
Selling online						
	Discrimination	0.71	0.01	0.00	0.70	0.73
	Difficulty	1.77	0.02	0.00	1.73	1.80
Using online learning resources						
	Discrimination	1.21	0.01	0.00	1.19	1.23
	Difficulty	1.56	0.01	0.00	1.54	1.58

Internet banking					
Discrimination	1.06	0.01	0.00	1.04	1.07
Difficulty	-0.56	0.01	0.00	-0.57	-0.55
Used word processing software					
Discrimination	3.34	0.02	0.00	3.29	3.38
Difficulty	-0.38	0.00	0.00	-0.38	-0.37
Used spreadsheet software					
Discrimination	2.86	0.02	0.00	2.82	2.90
Difficulty	0.16	0.00	0.00	0.15	0.17
Used software to edit photos, videos or audio files					
Discrimination	2.08	0.01	0.00	2.06	2.10
Difficulty	0.28	0.00	0.00	0.27	0.28
Created presentation or document integrating text, pictures, tables or charts					
Discrimination	2.71	0.02	0.00	2.67	2.74
Difficulty	0.27	0.00	0.00	0.26	0.27
Used advanced functions of spreadsheet to organise and analyse data					
Discrimination	2.82	0.02	0.00	2.78	2.87
Difficulty	0.62	0.00	0.00	0.62	0.63
Have written a code in a programming language					
Discrimination	1.85	0.02	0.00	1.81	1.88
Difficulty	2.07	0.01	0.00	2.04	2.09

Note: Number of observations = 587,749. Models weighted for population size.

Table A2: Descriptive statistics on the estimated level of digital skill, pooled sample

Category	Level of digital skill
Overall	2
Gender	
Men	2.1
Women	1.9
Age	
16-24	2.4
25-34	2.32
35-44	2.07
45-54	1.86
55-64	1.61
65-74	1.41
Education	
At most lower secondary	1.55
Upper secondary and post-secondary non-tertiary	1.89
Tertiary	2.5
Lower than tertiary	
Employment Status	
Employed	2.11
Unemployed	1.73
Student	2.54
Other not in labour force	1.43
Occupation	
Non-manual workers	2.31
Manual workers	1.55
Country	
AT	2.17
BE	2
BG	1.48
CY	1.72
CZ	1.89
DE	2.2
DK	2.39
EE	2.12
EL	1.9
ES	1.97
FI	2.35
FR	1.94
HR	2.16
HU	1.96
IE	1.84
IT	1.73
LT	2.05
LU	2.32
LV	1.83
MT	2.03
NL	2.41
PL	1.71
PT	2.04
RO	1.59
SE	2.27
SI	1.99
SK	1.91

Note: Data shown for they pooled sample including the years 2015, 2016, 2017 and 2019.

Table A3: Results of OLS regression on digital skill, 2015-2019, respondents 16-74

Y = Digital skill level	**Coeff**	**Std.dev.**
Female	-0.265***	-0.00412
Age (ref = 16-24):		
25-34	-0.149***	-0.0106
35-44	-0.337***	-0.0108
45-54	-0.529***	-0.0106
55-64	-0.703***	-0.011
65-74	-0.781***	-0.0128
Education (ref = At most lower secondary):		
Upper secondary and post-secondary non-tertiary	0.408***	-0.00608
Tertiary	0.913***	-0.00679
Employment status (ref = Employed manual):		
Employed non-manual	0.525***	-0.00652
Unemployed	0.185***	-0.00972
Student	0.788***	-0.0122
Other not in labour force	0.128***	-0.00827
Year	0.0132***	-0.00135
Country (ref = AT):		
BE	-0.101***	-0.0116
BG	-0.697***	-0.0106
CY	-0.521***	-0.0118
CZ	-0.166***	-0.0111
DE	0.147***	-0.00983
DK	0.340***	-0.0125
EE	-0.0269**	-0.0116
EL	-0.275***	-0.0119
ES	-0.0903***	-0.0108
FI	0.279***	-0.013
FR	-0.115***	-0.0106
HR	0.0984***	-0.0166
HU	-0.117***	-0.0119
IE	-0.312***	-0.013
IT	-0.264***	-0.00987
LT	-0.177***	-0.0118
LU	0.154***	-0.0155
LV	-0.307***	-0.0105
MT	-0.0199	-0.0178
NL	0.346***	-0.0113
PL	-0.452***	-0.0106
PT	0.0304**	-0.0124
RO	-0.504***	-0.00994
SE	0.159***	-0.0181
SI	-0.109***	-0.0157
SK	-0.255***	-0.0122
Constant	-24.95***	-2.723
Observations	583,093	
R-squared	0.356	

Note: *** p<0.01, ** p<0.05, * p<0.1. Model is weighted by population size.

Table A4: Matching rate between longitudinal and cross-sectional SILC

	Wave		
Country	2013	2016	2019
AT	91.5%	96.5%	96.5%
BE	87.1%	97.2%	96.1%
BG	95.7%	88.9%	94.2%
CY	69.2%	96.4%	95.9%
CZ	96.9%	96.5%	95.9%
DK	92.4%	97.9%	97.0%
EE	96.4%	95.9%	95.0%
EL	87.1%	97.2%	96.1%
ES	64.1%	94.3%	94.4%
FI	97.3%	97.1%	97.7%
FR	91.5%	96.5%	96.5%
HR	96.1%	96.1%	94.8%
HU	87.0%	95.7%	95.1%
IE	92.4%	92.3%	96.1%
IT	87.3%	87.9%	89.6%
LT	95.8%	95.1%	95.4%
LU	97.6%	92.8%	97.9%
LV	94.6%	93.8%	94.9%
MT	31.0%	28.7%	13.0%
NL	97.6%	97.7%	95.7%
PL	96.9%	96.5%	95.9%
PT	88.4%	95.4%	94.3%
RO	93.5%	95.8%	96.0%
SE	96.8%	96.7%	96.7%
SI	96.8%	88.3%	96.6%
SK	95.4%	97.1%	99.8%

Appendix B. Descriptive statistics for the EU-SILC estimation samples

Table B1: Estimation sample size

	Wave			
Country	2013	2016	2019	Total
AT	2,323	1,986	2,149	6,458
BE	2,029	2,292	3,540	7,861
BG	2,626	6,398	6,375	15,399
CY	2,872	1,748	2,121	6,741
CZ	4,311	3,285	3,657	11,253
DK	1,480	1,987	1,650	5,117
EE	2,299	2,474	2,565	7,338
EL	2,365	4,152	9,465	15,982
ES	4,974	4,909	4,425	14,308
FI	4,254	4,025	3,596	11,875
FR	9,665	9,405	8,551	27,621
HR	2,318	2,026	3,773	8,117
HU	3,595	3,042	2,685	9,322
IE	750	1,298	964	3,012
IT	5,616	6,804	8,634	21,054
LT	2,700	1,960	2,039	6,699
LU	1,515	1,375	1,681	4,571
LV	2,611	2,207	2,223	7,041
MT	2,118	2,155	1,852	6,125
NL	3,535	3,373	4,623	11,531
PL	6,323	5,909	5,036	17,268
PT	2,699	3,253	6,563	12,515
RO	3,933	3,708	3,606	11,247
SE	1,972	1,597	1,660	5,229
SI	3,919	3,627	3,696	11,242
SK	2,929	2,992	6,681	12,602
Total	85,731	87,987	103,810	277,528

Table B2: Descriptive statistics, 2010-2013 wave, year 2013

			Wave: 2010-2013		Year 2010
Variable	**Obs**	**Mean**	**Std.Dev**	**Min**	**Max**
age	2,323	52.00	16.66	20	81
region_AT1	2,323	0.42	0.49	0	1
region_AT2	2,323	0.20	0.40	0	1
region_AT3	2,323	0.38	0.48	0	1
eduL	2,323	0.18	0.38	0	1
eduM	2,323	0.62	0.48	0	1
eduH	2,323	0.20	0.40	0	1
urban_1	0				
urban_2	0				
urban_3	0				
employment rate	2,305	0.54	0.50	0	1
isco08_1	0				
isco08_2	0				
isco08_3	0				
isco08_4	0				
isco08_5	0				
isco08_6	0				
isco08_7	0				
isco08_8	0				
isco08_9	0				
isco08_10	0				
gross earnings	2,323	21133	32633	0	623682
digital skills	1,979	1.82	0.55	0.73	3.40
robot density	2,323	2.04	6.70	0.00	24.31
digital K intensity	1,129	0.02	0.03	0.00	0.12

Source: Our computation on longitudinal EU-SILC data 2010-2013.

Table B3: Descriptive statistics, 2013-2016 wave, year 2013

		Wave:	2013-2016		Year 2013
Variable	**Obs**	**Mean**	**Std.Dev**	**Min**	**Max**
age	1,986	50.01	16.99	17	78
region_AT1	1,986	0.46	0.50	0	1
region_AT2	1,986	0.19	0.39	0	1
region_AT3	1,986	0.35	0.48	0	1
eduL	1,986	0.20	0.40	0	1
eduM	1,986	0.61	0.49	0	1
eduH	1,986	0.19	0.39	0	1
urban_1	1,986	0.28	0.45	0	1
urban_2	1,986	0.32	0.47	0	1
urban_3	1,986	0.40	0.49	0	1
employment rate	1,986	0.54	0.50	0	1
isco08_1	1,986	0.06	0.24	0	1
isco08_2	1,986	0.06	0.24	0	1
isco08_3	1,986	0.16	0.36	0	1
isco08_4	1,986	0.17	0.38	0	1
isco08_5	1,986	0.09	0.29	0	1
isco08_6	1,986	0.16	0.37	0	1
isco08_7	1,986	0.04	0.21	0	1
isco08_8	1,986	0.12	0.32	0	1
isco08_9	1,986	0.06	0.23	0	1
isco08_10	1,986	0.08	0.27	0	1
gross earnings	1,986	19179	25816	0	215307
digital skills	1,777	1.83	0.54	0.73	3.14
robot density	1,986	2.39	7.19	0.00	24.31
digital K intensity	1,016	0.02	0.03	0.00	0.12

Source: Our computation on longitudinal EU-SILC data 2013-2016.

Table B4: Descriptive statistics, 2016-2019 wave, year 2016

		Wave:	2016-2019		Year 2016
Variable	**Obs**	**Mean**	**Std.Dev**	**Min**	**Max**
age	2,149	49.91	16.90	17	78
region_AT1	2,149	0.45	0.50	0	1
region_AT2	2,149	0.20	0.40	0	1
region_AT3	2,149	0.35	0.48	0	1
eduL	2,149	0.16	0.37	0	1
eduM	2,149	0.52	0.50	0	1
eduH	2,149	0.32	0.47	0	1
urban_1	2,149	0.27	0.44	0	1
urban_2	2,149	0.28	0.45	0	1
urban_3	2,149	0.45	0.50	0	1
employment rate	2,149	0.58	0.49	0	1
isco08_1	2,149	0.08	0.27	0	1
isco08_2	2,149	0.06	0.23	0	1
isco08_3	2,149	0.16	0.37	0	1
isco08_4	2,149	0.17	0.37	0	1
isco08_5	2,149	0.10	0.30	0	1
isco08_6	2,149	0.15	0.36	0	1
isco08_7	2,149	0.04	0.20	0	1
isco08_8	2,149	0.12	0.33	0	1
isco08_9	2,149	0.05	0.22	0	1
isco08_10	2,149	0.07	0.26	0	1
gross earnings	2,149	23263	33290	0	450644
digital skills	1,911	1.98	0.57	0.77	3.44
robot density	2,149	3.53	10.16	0.00	33.09
digital K intensity	1,187	0.03	0.03	0.00	0.15

Source: Our computation on longitudinal EU-SILC data 2016-2019.

Appendix C. Illustrative econometric results and validation for one repetition of the concatenated analysis, pooled sample.

Step 1: Estimation of 2019 outcomes on 2016-2019 wave

The first step of the concatenated analysis involves estimating employment outcomes and earnings between 2016 and 2019, that is on those individuals that are observed in all years 2016-2019.[24]

We first estimate employment outcomes for the whole working age population, without controlling for the indicators of digital transformation on the demand side (i.e. demand of digital skills).[25] This allows us to predict employment outcomes for all individuals observed in 2016, irrespective of whether they are employed or not employed. We then run a second model for those observed as employed in 2016, which allows us to include the two indicators of digital transformation on the demand side (digital capital intensity and robot density, at the industry level). We use these estimates to replace the prediction of employment outcomes for those observed as employed in 2016.[26] Tables C1 and C2 report regression results for the two samples.

Considering the whole EU population, we observe a lower employment prospect for women, and especially those with young children. Poor health (that is, a condition limiting daily activities) is a strong predictor of employment three years later. There is a clear gradient for gross income, with higher incomes leading to a higher probability of being employed at the end of the period. Digital skills are found to have a positive effect, with little gradient by education.

Predictions for individuals observed as employed in the initial period are then replaced using a model estimated exclusively on this sample, also controlling for indicators of digital transformation on the demand side (Table C2).

[24] As this step does not rely on previous simulations, it leads to identical results in all Montecarlo runs.

[25] The youngest age observed in SILC is 17. We restrict age to be below 65 in 2019, so that the sample is between 17 and 61 (inclusive) in 2016, or between 21 and 64 (inclusive) in 2019.

[26] To be noted, the first step of estimating employment outcomes could have been performed on those observed as not employed in the initial period only (as we do for the earnings models – see below), given that we eventually use it only to predict employment outcomes for this group. However, running our model on this group only reduces sample size and variability, leading to non-convergence of the estimates for a number of countries.

Table C1: Estimation results for employment equation (logistic regression). Output: Observed employment in 2019. Sample: EU27 (excluding Germany) 2016-2019, working age population

Logistic regression			
	Number of observations		64,980
Outcome: Observed employment in 2019	Prob > chi2		0.000
	Pseudo R2		0.413
	Coef.	Std. Err.	
Employed (2016)	2.852***	0.049	
Age	0.325***	0.014	
Age squared	-0.004***	0.000	
Sex: Female (Ref: Male)	-0.423***	0.046	
Health: Strongly limiting (Ref: n.a.)	-1.346***	0.123	
Health: Limiting (Ref: n.a.)	-0.541***	0.101	
Health: Not limiting (Ref: n.a.)	-0.168*	0.089	
Education: Medium (Ref: Low)	0.013	0.066	
Education: High (Ref: Low)	0.182	0.141	
Household size	0.001	0.019	
Living in consensual union, legal basis (Ref: n.a.)	-0.932*	0.509	
Living in consensual union, no legal basis (Ref: n.a.)	-0.829	0.512	
Not living in consensual union (Ref: n.a.)	-0.767	0.507	
No. children 0-3	0.287**	0.111	
- interaction with Sex: Female	-0.388***	0.134	
No. children 4-6	0.082	0.110	
- interaction with Sex: Female	-0.419***	0.132	
Population density: High (Ref: n.a.)	-0.226	0.193	
Population density: Intermediate (Ref: n.a.)	-0.144	0.193	
Population density: Low (Ref: n.a.)	-0.051	0.192	
Gross income quintile: 2 (Ref: 1)	0.187***	0.068	
Gross income quintile: 3 (Ref: 1)	0.231***	0.067	
Gross income quintile: 4 (Ref: 1)	0.345***	0.069	
Gross income quintile: 5 (Ref: 1)	0.244***	0.075	
Digital skills	0.335***	0.067	
- interaction with Education: Medium	-0.061	0.052	
- interaction with Education: High	0.055	0.090	
Regional dummies (NUTS 2)	Yes		

Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Key: $^{*} = p < .1$, $^{**} = p < .05$, $^{***} = p < .01$

Source: Our computation on longitudinal EU-SILC data 2016-2019.

Table C2: Estimation results for employment equation (logistic regression). Output: Observed employment in 2019. Sample: EU27 (excluding Germany) 2016-2019, population observed as employed in 2016.

Logistic regression			
		Number of observations	43,184
Outcome: Observed employment in 2019		Prob > chi2	0.000
		Pseudo R2	0.157
	Coef.	Std. Err.	
Employed (2016)	0.000	(omitted)	
Occupation: 1 (ref: n.a.)	2.631**	1.155	
Occupation: 2 (ref: n.a.)	2.694**	1.148	
Occupation: 3 (ref: n.a.)	2.543**	1.149	
Occupation: 4 (ref: n.a.)	2.451**	1.150	
Occupation: 5 (ref: n.a.)	2.400**	1.150	
Occupation: 6 (ref: n.a.)	2.325**	1.159	
Occupation: 7 (ref: n.a.)	2.440**	1.139	
Occupation: 8 (ref: n.a.)	2.267**	1.140	
Occupation: 9 (ref: n.a.)	2.248**	1.139	
Age	0.514***	0.023	
Age squared	-0.006***	0.000	
Sex: Female (Ref: Male)	-0.665***	0.148	
Living in consensual union, legal basis (Ref: n.a.)	-0.895***	0.197	
Living in consensual union, no legal basis (Ref: n.a.)	-0.424***	0.137	
Not living in consensual union (Ref: n.a.)	-0.067	0.123	
Education: Medium (Ref: Low)	0.282	0.229	
Education: High (Ref: Low)	0.817*	0.487	
Household size	0.022	0.029	
Living in consensual union, legal basis	-1.409	0.932	
Living in consensual union, no legal basis	-1.409	0.935	
Not living in consensual union	-1.096	0.931	
No. children 0-3	0.175	0.148	
- interaction with Sex: Female	-0.590***	0.175	
No. children 4-6	-0.061	0.157	
- interaction with Sex: Female	-0.282	0.193	
Population density: High (Ref: n.a.)	-0.536**	0.250	
Population density: Intermediate (Ref: n.a.)	-0.581**	0.249	
Population density: Low (Ref: n.a.)	-0.362	0.247	
Gross income quintile: 2 (Ref: 1)	0.287***	0.107	
Gross income quintile: 3 (Ref: 1)	0.311	0.107	
Gross income quintile: 4 (Ref: 1)	0.609	0.112	
Gross income quintile: 5 (Ref: 1)	0.431	0.116	
Digital skills	-0.113	0.329	
- interaction with Education: Medium	0.160	0.117	
- interaction with Education: High	-0.037	0.164	
Changes in digital capital intensity	-0.366*	0.195	
- interaction with Education: Medium	0.537**	0.231	
- interaction with Education: High	0.565**	0.249	
Changes in robot density	-0.012	0.011	
- interaction with Education: Medium	0.010	0.011	
- interaction with Education: High	0.002	0.013	

Regional dummies (NUTS 2)	Yes

Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Key: $^{*} = p < .1$, $^{**} = p < .05$, $^{***} = p < .01$

Source: Our computation on longitudinal EU-SILC data 2016-2019.

In this sample, restricted to employed individuals, the supply of digital skills is no longer significant. On the demand side, changes in digital capital intensity in the original sector of work are found to be negatively correlated with the probability of remaining employed at the end of the period, especially for those with low education. The suggestion from this analysis on the 2016-2019 period is that digital skills are important for finding a job, less so for retaining it, while industry evolution (that is, the indicators of digital transformation on the demand side) plays a bigger role in determining individual outcomes for those employed.

Overall, the fit of the two models combined (that for the whole population and that for employed workers only) is good: the predicted employment rate in 2019, in the age group considered, is 70.1%, against an observed employment rate of 70.4%.

We then estimate, on the 2016-2019 sample, a wage equation for gross and net earnings, where the outcome is the observed percentage changes in earnings between 2016 and 2019 (see eq. 2).[27]

The models are estimated separately for the sample of not employed in 2016 and for the sample of employed in 2016. In the latter, as in the specification for employment state, we also control for indicators of digital transformation on the demand side. Regression results for gross earnings are reported in Tables C3 and C4, for the two samples respectively.

[27] As discussed in the text, changes in earnings are approximated by the inverse hyperbolic sine transformation.

Table C3: Estimation results for gross earnings (linear regression). Output: Changes in transformed gross yearly earnings (inverse hyperbolic syne transformation) between 2016 and 2019. Sample: population observed as not employed in 2016.

Linear regression			
Outcome: Gross earnings growth 2016-2019	Number of observations		21,773
	Prob > F		0
	R2		0.124
	Coef.	Std. Err.	
Employed (2019)	0.327***	0.035	
Employed (2016)	0.000	(omitted)	
Age	0.003	0.013	
Age squared	0.000	0.000	
Sex: Female (Ref: Male)	0.068*	0.040	
Health: Strongly limiting (Ref: n.a.)	-0.402***	0.101	
Health: Limiting (Ref: n.a.)	-0.419***	0.117	
Health: Not limiting (Ref: n.a.)	-0.353***	0.097	
Education: Medium (Ref: Low)	-0.080	0.059	
Education: High (Ref: Low)	-0.155	0.127	
Household size	0.037***	0.014	
Living in consensual union, legal basis (Ref: n.a.)	0.198	0.238	
Living in consensual union, no legal basis (Ref: n.a.)	0.028	0.245	
Not living in consensual union (Ref: n.a.)	-0.044	0.233	
No. children 0-3	0.061	0.177	
- interaction with Sex: Female	-0.132	0.187	
No. children 4-6	-0.187**	0.081	
- interaction with Sex: Female	0.103	0.089	
Population density: High (Ref: n.a.)	0.380**	0.163	
Population density: Intermediate (Ref: n.a.)	0.344**	0.164	
Population density: Low (Ref: n.a.)	0.370**	0.163	
Gross income quintile: 2 (Ref: 1)	-0.749***	0.060	
Gross income quintile: 3 (Ref: 1)	-0.855***	0.059	
Gross income quintile: 4 (Ref: 1)	-0.936***	0.063	
Gross income quintile: 5 (Ref: 1)	-1.119***	0.065	
Digital skills	0.180***	0.066	
- interaction with Education: Medium	-0.047	0.035	
- interaction with Education: High	0.030	0.083	
Regional dummies (NUTS 2)	Yes		

Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Key: * = p < .1, ** = p < .05, *** = p < .01

Source: Our computation on longitudinal EU-SILC data 2016-2019.

Table C4: Estimation results for gross earnings (linear regression). Output: Changes in transformed gross yearly earnings (inverse hyperbolic syne transformation) between 2016 and 2019. Sample: population observed as employed in 2016.

Linear regression			
Outcome: Gross earnings growth 2016-2019		Number of observations	43,186
		Prob > F	0.000
		R2	0.116
	Coef.	Std. Err.	
Employed (2019)	0.180301***	0.022218	
Employed (2016)	0	(omitted)	
Occupation: 1 (ref: n.a.)	0.067626	0.155881	
Occupation: 2 (ref: n.a.)	0.067125	0.154787	
Occupation: 3 (ref: n.a.)	0.021926	0.155139	
Occupation: 4 (ref: n.a.)	0.007701	0.155496	
Occupation: 5 (ref: n.a.)	-0.02651	0.155667	
Occupation: 6 (ref: n.a.)	-0.14592	0.157869	
Occupation: 7 (ref: n.a.)	-0.08526	0.1536	
Occupation: 8 (ref: n.a.)	-0.05001	0.153428	
Occupation: 9 (ref: n.a.)	-0.10135	0.154107	
Age	-0.01397***	0.00424	
Age squared	0.000124**	4.87E-05	
Sex: Female (Ref: Male)	-0.0415*	0.021428	
Living in consensual union, legal basis (Ref: n.a.)	-0.08341**	0.037662	
Living in consensual union, no legal basis (Ref: n.a.)	-0.09354***	0.025115	
Not living in consensual union (Ref: n.a.)	-0.06292***	0.022138	
Education: Medium (Ref: Low)	0.097669**	0.037892	
Education: High (Ref: Low)	0.123823	0.075685	
Household size	0.047008***	0.004685	
Living in consensual union, legal basis	-0.02565	0.077111	
Living in consensual union, no legal basis	-0.07469	0.07798	
Not living in consensual union	-0.12902*	0.077423	
No. children 0-3	-0.04017***	0.011644	
- interaction with Sex: Female	0.015066	0.01532	
No. children 4-6	-0.04465***	0.015579	
- interaction with Sex: Female	-0.00319	0.022921	
Population density: High (Ref: n.a.)	-0.01486	0.034872	
Population density: Intermediate (Ref: n.a.)	-0.02324	0.035752	
Population density: Low (Ref: n.a.)	-0.01737	0.035538	
Gross income quintile: 2 (Ref: 1)	-0.41954***	0.032656	
Gross income quintile: 3 (Ref: 1)	-0.52043***	0.031253	
Gross income quintile: 4 (Ref: 1)	-0.61107***	0.032134	
Gross income quintile: 5 (Ref: 1)	-0.77371***	0.033557	
Digital skills	-0.07917	0.05279	
- interaction with Education: Medium	0.035267	0.027934	
- interaction with Education: High	0.068084*	0.035952	
Changes in digital capital intensity	0.025106	0.054982	
- interaction with Education: Medium	-0.02705	0.057724	
- interaction with Education: High	-0.02203	0.058441	
Changes in robot density	-0.00103	0.002244	

- interaction with Education: Medium	0.001282	0.002295
- interaction with Education: High	0.000863	0.002344
Regional dummies (NUTS 2)	Yes	

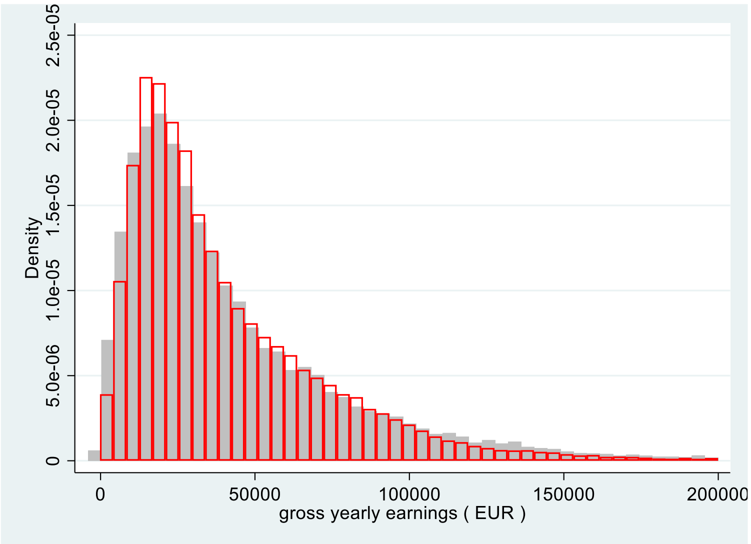
Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Key: * = $p < .1$, ** = $p < .05$, *** = $p < .01$

Source: Our computation on longitudinal EU-SILC data 2016-2019.

After controlling for the employment state in the end period, few variables are significant. Among those, digital skills for individuals with high education are positively associated to earnings gains, if not employed in 2016, but no association is detected for those employed. At the EU level, indicators of demand for digital skills (changes in digital capital intensity and robot density) have little bearing on changes in earnings. To validate the model, we compare the observed and predicted distribution of earnings (Figure C1).

Figure C1: Step 1 - Gross earnings fit for 2019, based on 2016 characteristics. EU27 2016-2019 sample



Gray: observed distribution. Red: estimated distribution. 2016-2019 sample aged between 17 and 61 in 2016.

Source: Our computation on longitudinal EU-SILC data 2016-2019.

The mean of predicted yearly gross earnings is EUR 41,974, against EUR 44,966 for observed earnings, in the sample; the estimated median is EUR 31,414, against EUR 30,510 for the observed median.

Regression results for net earnings are reported in Tables C5 and C6, for the two samples respectively. The explanatory power of the specification for net earnings (as measured by the R2) is lower than for gross earnigns, as expected, given that the operation of the welfare state is explicitly aimed at attenuating the effects of individual characteristics (and shocks) on outcomes. The results obtained for gross earnings are, however, broadly confirmed also for net earnings, with the initial level of digitals skills having a positive effect on earning growth for those not in employment in the initial period, but not for those initially observed as employed.

Table C5: Estimation results for net earnings (linear regression). Output: Changes in transformed net yearly earnings (inverse hyperbolic syne transformation) between 2016 and 2019. Sample: population observed as not employed in 2016.

Linear regression			
Outcome: Net earnings growth 2016-2019		Number of observations	21,783
		Prob > F	0
		R2	0.091
	Coef.	Std. Err.	
Employed (2019)	0.337005***	0.0425864	
Employed (2016)	0	(omitted)	
Age	0.003	0.017	
Age squared	0.000	0.000	
Sex: Female (Ref: Male)	0.067	0.054	
Health: Strongly limiting (Ref: n.a.)	-0.444***	0.116	
Health: Limiting (Ref: n.a.)	-0.475***	0.126	
Health: Not limiting (Ref: n.a.)	-0.429***	0.108	
Education: Medium (Ref: Low)	-0.107	0.084	
Education: High (Ref: Low)	-0.114	0.201	
Household size	0.034*	0.019	
Living in consensual union, legal basis (Ref: n.a.)	0.347	0.229	
Living in consensual union, no legal basis (Ref: n.a.)	0.038	0.245	
Not living in consensual union (Ref: n.a.)	0.121	0.223	
No. children 0-3	0.411	0.393	
- interaction with Sex: Female	-0.347	0.413	
No. children 4-6	-0.293**	0.133	
- interaction with Sex: Female	0.187	0.144	
Population density: High (Ref: n.a.)	0.219*	0.114	
Population density: Intermediate (Ref: n.a.)	0.234**	0.118	
Population density: Low (Ref: n.a.)	0.271**	0.114	
Gross income quintile: 2 (Ref: 1)	-0.816***	0.078	

Gross income quintile: 3 (Ref: 1)	-0.925***	0.080
Gross income quintile: 4 (Ref: 1)	-1.019***	0.088
Gross income quintile: 5 (Ref: 1)	-1.180	0.089
Digital skills	0.219	0.110
- interaction with Education: Medium	-0.048	0.051
- interaction with Education: High	0.023	0.101
Regional dummies (NUTS 2)	yes	

Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Key: * = $p < .1$, ** = $p < .05$, *** = $p < .01$

Source: Our computation on longitudinal EU-SILC data 2016-2019.

Table C6: Estimation results for net earnings (linear regression). Output: Changes in transformed net yearly earnings (inverse hyperbolic syne transformation) between 2016 and 2019. Sample: population observed as employed in 2016.

Linear regression			
	Number of observations		43,191
Outcome: Net earnings growth 2016-2019	Prob > F		0.000
	R2		0.057
	Coef.	Std. Err.	
Employed (2019)	0.151***	0.027	
Employed (2016)	0.000	(omitted)	
Occupation: 1 (ref: n.a.)	0.088	0.148	
Occupation: 2 (ref: n.a.)	0.037	0.139	
Occupation: 3 (ref: n.a.)	0.005	0.142	
Occupation: 4 (ref: n.a.)	-0.032	0.142	
Occupation: 5 (ref: n.a.)	-0.035	0.142	
Occupation: 6 (ref: n.a.)	-0.135	0.145	
Occupation: 7 (ref: n.a.)	-0.081	0.138	
Occupation: 8 (ref: n.a.)	-0.040	0.138	
Occupation: 9 (ref: n.a.)	-0.099	0.140	
Age	-0.024***	0.006	
Age squared	0.000***	0.000	
Sex: Female (Ref: Male)	-0.035	0.031	
Living in consensual union, legal basis (Ref: n.a.)	-0.055	0.057	
Living in consensual union, no legal basis (Ref: n.a.)	-0.102**	0.041	
Not living in consensual union (Ref: n.a.)	-0.067*	0.037	
Education: Medium (Ref: Low)	0.086*	0.045	
Education: High (Ref: Low)	0.113	0.095	
Household size	0.045***	0.006	
Living in consensual union, legal basis	0.001	0.073	
Living in consensual union, no legal basis	-0.039	0.075	
Not living in consensual union	-0.132*	0.073	
No. children 0-3	-0.041***	0.014	

- interaction with Sex: Female	0.015	0.018
No. children 4-6	-0.049***	0.017
- interaction with Sex: Female	-0.003	0.025
Population density: High (Ref: n.a.)	0.065	0.044
Population density: Intermediate (Ref: n.a.)	0.041	0.045
Population density: Low (Ref: n.a.)	0.058	0.045
Gross income quintile: 2 (Ref: 1)	-0.437***	0.045
Gross income quintile: 3 (Ref: 1)	-0.565***	0.041
Gross income quintile: 4 (Ref: 1)	-0.629***	0.041
Gross income quintile: 5 (Ref: 1)	-0.815***	0.045
Digital skills	-0.050	0.061
- interaction with Education: Medium	0.016	0.031
- interaction with Education: High	0.052	0.044
Changes in digital capital intensity	0.044	0.060
- interaction with Education: Medium	-0.055	0.062
- interaction with Education: High	-0.051	0.064
Changes in robot density	-0.001	0.002
- interaction with Education: Medium	0.001	0.002
- interaction with Education: High	0.001	0.002
Regional dummies (NUTS 2)	Yes	

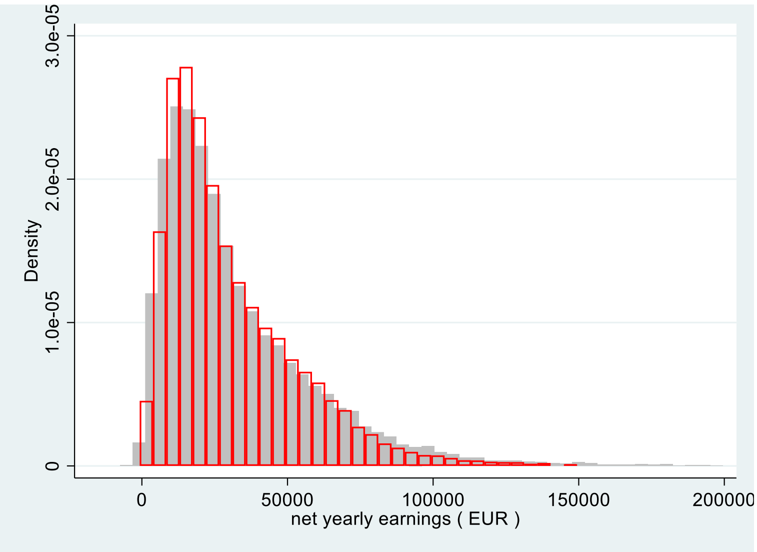
Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Key: $^{*} = p < .1$, $^{**} = p < .05$, $^{***} = p < .01$

Source: Our computation on longitudinal EU-SILC data 2016-2019.

Despite the lower explanatory power, the fit of the net earnings equation is still very good, as shown in Figure C2.

Figure C2: Step 1 - Net earnings fit for 2019, based on 2016 characteristics. EU27 2016-2019 sample



Gray: observed distribution. Red: estimated distribution: 2016-2019 sample aged between 17 and 61 in 2016.

Source: Our computation on longitudinal EU-SILC data 2016-2019.

The mean of predicted yearly gross earnings is EUR 31,638, against EUR 33,379 for observed earnings, in the sample; the estimated median is EUR 24,123, against EUR 24,677 for the observed median.

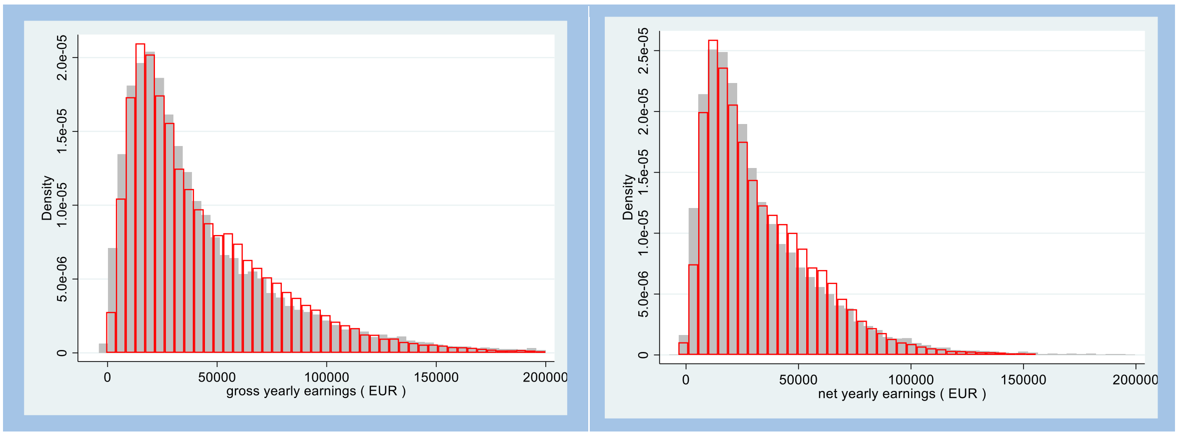
Step 2: Simulation of 2019 outcomes on 2013-2016 wave, based on the results of Step 1

The next step is using the estimates obtained in Step 1 to simulate 2019 outcomes on the 2013-2016 wave. This is possible because in that wave we have individuals who are observed in all years 2013-2016. For these individuals, information is available on their characteristics in 2016. This allows to use the Step 1 models to make predictions for the 2013-2016 population.

To be stressed again, the employment transition logit model predicts the probability of employment. We use this probability to simulate the outcome (either employed or not employed) with a Montecarlo draw. Results therefore also depend, in addition to the distributional characteristics of the population of the 2013-2016 wave (which might be different from those of the 2016-2019 wave, see Tables in Appendix B) on a stochastic element, which is the motivation for our bootstrapping strategy. With the specific draw of the example, we obtain an average simulated employment rate in 2019, in the EU27, of 73.5% for the 2013-2016 sample aged between 17 (in 2013) and 61 (in 2016), who would have been between 20 in 2016 and 64 in 2019. By comparison, the observed employment rate in 2019 for the 2016-2019 sample aged between 20 (in 2016) and 64 (in 2019) is 70.4%. The difference is partly attributable to differences in the characteristics of the two samples, and in particular to an evolving age structure due to population ageing (see again the descriptive statistics in Appendix B), which in itself drives employment rates down, and partly to the specific random draws used for the Montecarlo simulation.

The gross earnings distribution for 2019 simulated on the 2013-2016 sample looks remarkably similar to the observed distribution for the 2016-2019 sample, despite the differences in the two populations (Figure C3).[28]

Figure C3: Step 2 - Observed and simulated 2019 earnings distribution, gross (left panel) and net (right panel)



Gray: observed distributions, 2016-2019 sample. Red: simulated distributions, 2013-2016 sample. All individuals aged between 17 and 61 in 2016. The simulated distributions are the counterpart on the 2013-2016 sample of the estimated distributions: they are obtained applying the same estimated coefficients from Step 1, but on the 2013-2016 sample.

Source: Our computation on longitudinal EU-SILC data 2013-2019.

Step 3: Estimation of 2019 (projected) outcomes on 2013-2016 wave

Step 3 is again an estimation step, where the simulated 2019 outcomes for the 2013-2016 wave – as computed in Step 2 – are regressed against 2013 inputs.

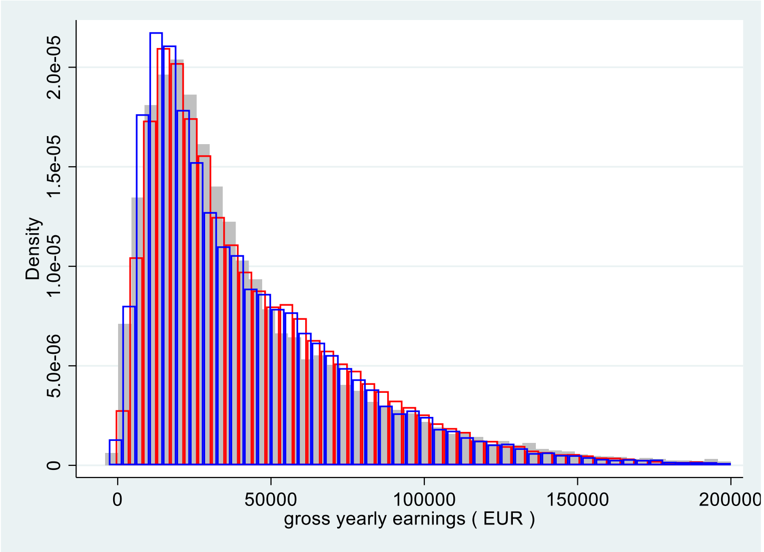
Estimates of the employment equation show a good fit, with a target rate of 73.5% (see Step 2) and a predicted rate of 72.9%.[29]

We then estimate our wage equations, where the outcome is simulated changes in (gross and net) earnings between 2013 and 2019, as computed in Step 2. The goal is to obtain coefficients that can then be applied to the 2010-2013 sample. Figure C4 shows the observed distribution of 2019 gross earnings (in gray), superimposed to the simulated distribution of 2019 gross earnings for the 2013-2016 sample, and the estimated distribution for the same sample (in blue). The three distributions are broadly comparable.

[28] Different random draws for the Montecarlo simulation of employment outputs lead to slightly different estimated distributions of earnings. This is because the earnings regressions control for employment outputs. The results shown here refer to a single repetition of the Montecarlo simulation.

[29] Estimation results are available upon request.

Figure C4: Step 3 - Earnings equation fit for 2019 gross earnings, based on 2013 characteristics. EU27 2013-2019 sample

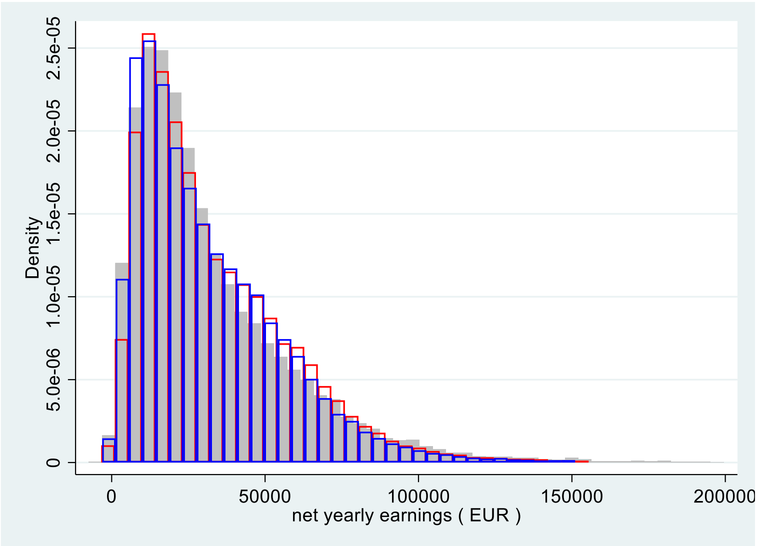


Gray: observed distribution, 2016-2019 sample. Red: simulated distribution, 2013-2016 sample. Blue: estimated distribution, 2013-2016 sample. All individuals aged between 17 and 61 in 2016. The simulated distribution in red is the same as in Figure 7.

Source: Our computation on longitudinal EU-SILC data 2013-2019.

The same is true for net earnings (Figure C5).

Figure C5: Step 3 - Wage equation fit for 2019 net earnings, based on 2013 characteristics. EU27 2013-2019 sample



Gray: observed distribution, 2016-2019 sample. Red: simulated distribution, 2013-2016 sample. Blue: estimated distribution, 2013-2016 sample. All individuals aged between 17 and 61 in 2016. The simulated distribution in red is the same as in Figure 7.

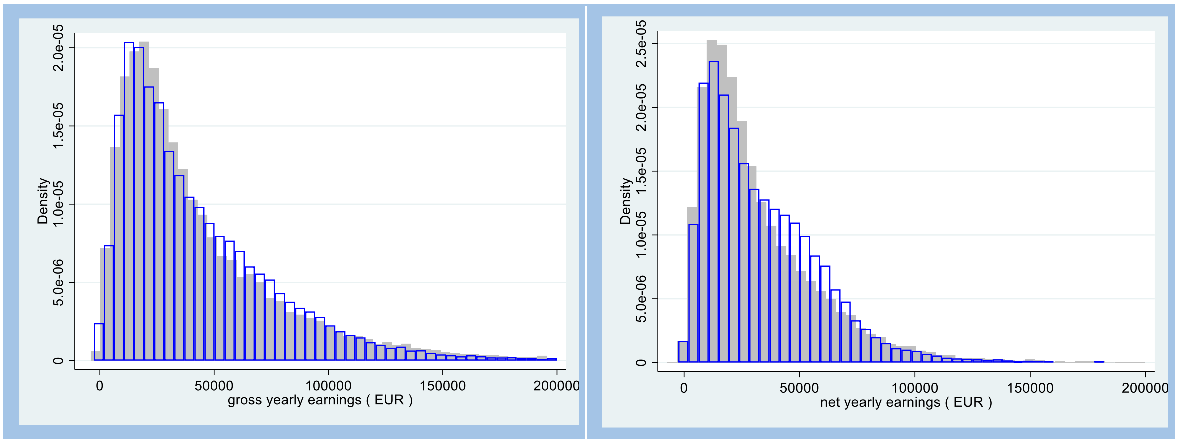
Source: Our computation on longitudinal EU-SILC data 2013-2019.

Step 4: Prediction of 2019 outcomes on 2010-2013 wave, based on the results of Step 3

Step 4 involves applying the estimates from Step 3 to the 2010-2013 sample, in order to obtain projected outcomes in 2019 for this sample. To this aim, we exploit the fact that both the 2010-2013 sample and the 2013-2016 sample contain individuals observed in 2013. With the specific Montecarlo draws used for the simulation, we obtain a simulated employment rate in 2019 of 75.2% for the 2010-2013 sample, against a target of 72.9% on the 2013-2016 sample. Again, the difference is attributable to differences in the characteristics of the two samples, in addition to the randomness in the Montecarlo procedure for attribution of employment states based on the estimated employment probabilities.

The gross earnings distribution for 2019 simulated on the 2010-2013 sample and the observed distribution for the 2016-2019 sample are depicted in Figure C6, for both gross and net earnings. The longer time gap between the two samples contributes to differentiate them (in addition to the Montecarlo variability).

Figure C6: Step 4 - Observed and simulated 2019 earnings distribution, gross (left panel) and net (right panel)



Gray: observed distributions, 2016-2019 sample. Blue: simulated distributions, 2010-2013 sample. All individuals aged between 17 and 58 in 2013. The simulated distributions are the counterpart on the 2010-2013 sample of the estimated distributions in blue of Figures 8 and 9: they are obtained applying the same estimated coefficients from Step 3, but on the 2010-2013 sample.

Source: Our computation on longitudinal EU-SILC data 2010-2019.

Step 5: Estimation of 2019 (projected) outcomes on 2010-2013 wave

Finally, in Step 5 we estimate the relationships of interest, the effects of digital intensity over the decade 2010-2019, for the 2010 population. Estimates from the employment equations, where the outcome is simulated employment in 2019, are reported in Tables C7 and C8, respectively for the whole population and the population of individuals observed as employed in 2010. The analysis confirms qualitatively the results for the 2016-2019 sample: the probability of being in employment in 2019 depends positively on being already employed in 2010 and on initial income, with a substantial gender gap, especially for families with young children; there is a positive effect of endowments in digital skills with limited or no educational gradient for the whole sample, but not for the sample of those starting as employed (implying strong effects of digital skills for those not in employment); indicators of demand for digital skills are not significant. Hence, the conclusion from the analysis on the whole period 2010-2019 – for the specific Montecarlo draw considered here – reinforces results from the sub-periods: digital skills are important for finding a job, less so for retaining it.

Table C7: Estimation results for employment equation (logistic regression). Output: Simulated employment in 2019. Sample: EU27 (excluding Germany), working age population.

Logistic regression		
Outcome: Simulatred employment in 2019	Number of observations	51,034
	Prob > chi2	0.000
	Pseudo R2	0.206

	Coef.	Std. Err.
Employed (2010)	0.901***	0.049
Age	0.372***	0.016
Age squared	-0.005***	0.000
Sex: Female (Ref: Male)	-0.712***	0.044
Health: Strongly limiting (Ref: n.a.)	-0.403***	0.126
Health: Limiting (Ref: n.a.)	-0.280***	0.105
Health: Not limiting (Ref: n.a.)	-0.047	0.089
Education: Medium (Ref: Low)	-0.041	0.059
Education: High (Ref: Low)	0.280*	0.143
Household size	0.029*	0.017
Living in consensual union, legal basis (Ref: n.a.)	1.449**	0.632
Living in consensual union, no legal basis (Ref: n.a.)	1.601**	0.635
Not living in consensual union (Ref: n.a.)	1.644***	0.633
No. children 0-3	0.127	0.086
- interaction with Sex: Female	-0.328***	0.102
No. children 4-6	0.165*	0.094
- interaction with Sex: Female	-0.172	0.114
Population density: High (Ref: n.a.)	-0.074	0.149
Population density: Intermediate (Ref: n.a.)	-0.013	0.151
Population density: Low (Ref: n.a.)	0.048	0.150
Gross income quintile: 2 (Ref: 1)	0.142**	0.061
Gross income quintile: 3 (Ref: 1)	0.380***	0.060
Gross income quintile: 4 (Ref: 1)	0.512***	0.065
Gross income quintile: 5 (Ref: 1)	0.525***	0.072
Digital skills	0.411***	0.064
- interaction with Education: Medium	-0.010	0.056
- interaction with Education: High	-0.086	0.111
Regional dummies (NUTS 2)	Yes	

Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Key: $^{*} = p < .1$, $^{**} = p < .05$, $^{***} = p < .01$

Source: Our computation on longitudinal EU-SILC data 2010-2019.

Table C8: Estimation results for employment equation (logistic regression). Output: Simulated employment in 2019. Sample: EU27 (excluding Germany), individuals observed as employed in 2010.

Logistic regression			
Outcome: Simulated employment in 2019		Number of observations	34,233
		Prob > chi2	0.000
		Pseudo R2	0.175
	Coef.	Std. Err.	
Employed (2010)	0.000	(omitted)	
Occupation: 1 (ref: n.a.)	-0.130	0.296	
Occupation: 2 (ref: n.a.)	0.023	0.280	
Occupation: 3 (ref: n.a.)	0.034	0.274	
Occupation: 4 (ref: n.a.)	-0.039	0.276	
Occupation: 5 (ref: n.a.)	-0.207	0.275	
Occupation: 6 (ref: n.a.)	-0.180	0.288	
Occupation: 7 (ref: n.a.)	-0.106	0.290	
Occupation: 8 (ref: n.a.)	-0.328	0.292	
Occupation: 9 (ref: n.a.)	-0.277	0.294	
Age	0.467***	0.024	
Age squared	-0.007***	0.000	
Sex: Female (Ref: Male)	-0.870***	0.107	
Living in consensual union, legal basis (Ref: n.a.)	0.005	0.193	
Living in consensual union, no legal basis (Ref: n.a.)	-0.126	0.137	
Not living in consensual union (Ref: n.a.)	0.002	0.114	
Education: Medium (Ref: Low)	0.164	0.159	
Education: High (Ref: Low)	0.747**	0.340	
Household size	0.020	0.025	
Living in consensual union, legal basis	0.657	0.817	
Living in consensual union, no legal basis	0.822	0.820	
Not living in consensual union	0.862	0.819	
No. children 0-3	0.115	0.100	
- interaction with Sex: Female	-0.250*	0.133	
No. children 4-6	0.081	0.110	
- interaction with Sex: Female	-0.093	0.144	
Population density: High (Ref: n.a.)	-0.245	0.180	
Population density: Intermediate (Ref: n.a.)	-0.210	0.182	
Population density: Low (Ref: n.a.)	-0.119	0.182	
Gross income quintile: 2 (Ref: 1)	0.211**	0.089	
Gross income quintile: 3 (Ref: 1)	0.351***	0.088	
Gross income quintile: 4 (Ref: 1)	0.457***	0.093	
Gross income quintile: 5 (Ref: 1)	0.577***	0.105	
Digital skills	0.127	0.220	
- interaction with Education: Medium	0.044	0.111	
- interaction with Education: High	-0.126	0.168	
Changes in digital capital intensity	0.018	0.119	
- interaction with Education: Medium	0.081	0.131	
- interaction with Education: High	0.084	0.200	
Changes in robot density	-0.007	0.006	
- interaction with Education: Medium	0.004	0.006	
- interaction with Education: High	-0.002	0.007	

Regional dummies (NUTS 2)	Yes

Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Key: $^{*} = p < .1$, $^{**} = p < .05$, $^{***} = p < .01$

Source: Our computation on longitudinal EU-SILC data 2010-2019.

Tables C9 and C10 show the results from the analysis of the effects of digital transformation on gross earnings. In this specific Montecarlo draw, results from our initial analysis on the period 2016-2019 are qualitatively confirmed. Individuals with higher levels of digital skills who are not employed in the initial period experience more earnings growth, and the effect is stronger for lower levels of education. As with respect to the indicators of demand for digital skills, in this Montecarlo draw we find that changes in digital capital intensity in the past decade are positively associated with growth in gross earnings, while changes in robot density are negatively associated with growth in gross earnings, but these effects are detectable only for the low educated.

Table C9: Estimation results for gross earnings (linear regression). Output: Changes in transformed gross yearly earnings (inverse hyperbolic syne transformation) between 2010 and 2019. Sample: EU27 (excluding Germany), population observed as not employed in 2010.

Linear regression		
Outcome: Simulated gross earnings growth 2010-2019	Number of observations	16,330
	Prob > F	0.000
	R2	0.633

	Coef.	Std. Err.
Employed (2019)	0.134***	0.005
Employed (2010)	0.000	(omitted)
Age	-0.002	0.002
Age squared	0.000	0.000
Sex: Female (Ref: Male)	0.014**	0.006
Health: Strongly limiting (Ref: n.a.)	-0.005	0.012
Health: Limiting (Ref: n.a.)	0.009	0.012
Health: Not limiting (Ref: n.a.)	0.021**	0.010
Education: Medium (Ref: Low)	-0.034***	0.007
Education: High (Ref: Low)	-0.041***	0.015
Household size	-0.007***	0.002
Living in consensual union, legal basis (Ref: n.a.)	0.034	0.034
Living in consensual union, no legal basis (Ref: n.a.)	-0.020	0.035
Not living in consensual union (Ref: n.a.)	-0.049	0.035
No. children 0-3	0.019	0.011
- interaction with Sex: Female	0.012	0.012
No. children 4-6	0.026*	0.015
- interaction with Sex: Female	-0.011	0.016
Population density: High (Ref: n.a.)	-0.105***	0.017
Population density: Intermediate (Ref: n.a.)	-0.140***	0.017
Population density: Low (Ref: n.a.)	-0.128***	0.017
Gross income quintile: 2 (Ref: 1)	-0.118***	0.007
Gross income quintile: 3 (Ref: 1)	-0.218***	0.007
Gross income quintile: 4 (Ref: 1)	-0.270***	0.008
Gross income quintile: 5 (Ref: 1)	-0.309***	0.009
Digital skills	0.017**	0.009
- interaction with Education: Medium	0.008*	0.005
- interaction with Education: High	-0.01087	0.0091286
Regional dummies (NUTS 2)	Yes	

Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Key: * = $p < .1$, ** = $p < .05$, *** = $p < .01$

Source: Our computation on longitudinal EU-SILC data 2010-2019.

Table C10: Estimation results for gross earnings (linear regression). Output: Changes in transformed gross yearly earnings (inverse hyperbolic syne transformation) between 2010 and 2019. Sample: EU27 (excluding Germany), population observed as employed in 2010.

Linear regression		
	Number of observations	33,749
Outcome: Simulated gross earnings growth 2010-2019	Prob > F	0.000
	R2	0.679

	Coef.	Std. Err.
Employed (2019)	0.119***	0.004
Employed (2010)	0.000	(omitted)
Occupation: 1 (ref: n.a.)	0.017	0.013
Occupation: 2 (ref: n.a.)	0.015	0.013
Occupation: 3 (ref: n.a.)	0.006	0.013
Occupation: 4 (ref: n.a.)	0.000	0.013
Occupation: 5 (ref: n.a.)	0.017	0.013
Occupation: 6 (ref: n.a.)	-0.020	0.014
Occupation: 7 (ref: n.a.)	0.004	0.014
Occupation: 8 (ref: n.a.)	0.001	0.014
Occupation: 9 (ref: n.a.)	0.025*	0.014
Age	-0.004***	0.001
Age squared	0.000	0.000
Sex: Female (Ref: Male)	-0.013***	0.005
Living in consensual union, legal basis (Ref: n.a.)	-0.018*	0.009
Living in consensual union, no legal basis (Ref: n.a.)	-0.018***	0.006
Not living in consensual union (Ref: n.a.)	-0.019***	0.005
Education: Medium (Ref: Low)	0.002	0.008
Education: High (Ref: Low)	0.027*	0.015
Household size	0.009***	0.001
Living in consensual union, legal basis	0.016	0.017
Living in consensual union, no legal basis	-0.023	0.017
Not living in consensual union	-0.040**	0.017
No. children 0-3	0.025***	0.003
- interaction with Sex: Female	-0.009**	0.004
No. children 4-6	0.008**	0.003
- interaction with Sex: Female	-0.008*	0.004
Population density: High (Ref: n.a.)	-0.100***	0.007
Population density: Intermediate (Ref: n.a.)	-0.118***	0.007
Population density: Low (Ref: n.a.)	-0.103***	0.007
Gross income quintile: 2 (Ref: 1)	-0.094***	0.005
Gross income quintile: 3 (Ref: 1)	-0.165***	0.005
Gross income quintile: 4 (Ref: 1)	-0.207***	0.005
Gross income quintile: 5 (Ref: 1)	-0.253***	0.005
Digital skills	-0.014	0.011
- interaction with Education: Medium	0.006	0.006
- interaction with Education: High	0.004	0.007
Changes in digital capital intensity	0.019***	0.006
- interaction with Education: Medium	-0.019***	0.007
- interaction with Education: High	-0.025****	0.007
Changes in robot density	-0.002***	0.000

- interaction with Education: Medium		0.001***	0.000
- interaction with Education: High		0.001749	0.00027
Regional dummies (NUTS 2)	yes		

Note: Occupation grouped as follows: 1 = armed forces & managers; 2 = professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. P-values below .1 in bold.

Source: Our computation on longitudinal EU-SILC data 2010-2019.

The same is true with respect to net earnings (results not shown).

Appendix D. Results for net earnings

Table D1: Estimated coefficients for the effects of changes in digital capital intensity and robot density in the industry of employment in 2010 on (approximate) net earnings growth between 2010 and 2019. Sample: EU27 (excluding Germany).

		Digital capital intensity			**Robot density**	
Sample		employed			Employed	
Education	low	medium	high	low	medium	high
Mean effect	0.024	-0.005	-0.010	-0.0018	-0.0001	0.0001
Std.dev.	0.001	0.000	0.000	0.0000	0.0000	0.0000
Min	0.022	-0.006	-0.011	-0.0019	-0.0002	0.0001
Max	0.026	-0.003	-0.009	-0.0017	-0.0001	0.0002

Note: The table reports summary statistics for the estimated coefficients over 100 repetitions of the concatenated analysis from Step 5. The coefficients measure the approximate percentage change in gross yearly earnings (difference in inverse hyperbolic sine transformation) between 2010 and 2019 corresponding to a one standard deviation increase in the value of the index over the same period.

Source: Our computation on longitudinal EU-SILC data 2010-2019.

Table D2: Estimated coefficients for the effects of the 2010 endowment of digital skills on (approximate) net earnings growth between 2010 and 2019. Sample: EU27 (excluding Germany).

Sample		Not employed			Employed	
Education	low	medium	high	Low	medium	high
Mean effect	0.027	0.036	-0.006	-0.014	-0.012	-0.019
Std.dev.	0.001	0.002	0.001	0.001	0.001	0.001
Min	0.024	0.033	-0.009	-0.018	-0.015	-0.021
Max	0.031	0.040	-0.002	-0.009	-0.009	-0.016

Note: The table reports summary statistics for the estimated coefficients over 100 repetitions of the concatenated analysis from Step 5. The coefficients measure the approximate percentage change in net yearly earnings (difference in inverse hyperbolic sine transformation) between 2010 and 2019 corresponding to a one standard deviation increase in the value of the index.

Source: Our computation on longitudinal EU-SILC data 2010-2019.