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The impact of a decade of digital transformation on employment, wages, and inequality in the EU: a "conveyor belt" hypothesis

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Abstract

We study the effects of digital transformation in the European Union on individual employment outcomes, wage growth, and income inequality, during the decade 2010–9. Our results allow us to formulate a 'conveyor-belt' hypothesis suggesting that employment confers a competitive advantage in navigating the digital transition due to the accumulation of pertinent skills in the workplace. Because digital skills are acquired with the changing demands of the job, their initial endowment matters less for the employed than for the non-employed. Furthermore, 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 earnings 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.

Key words: digital transformation; digital skills; inequality; employment; wages; EU.

JEL classification: J24, J31, D31

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 digitalization on the labour market, looking for instance at job polarization, labour productivity, or employment (e.g. Fernández-Macías and Hurley 2016; Graetz and Michaels 2018; Georgieff and Hyee 2022). The majority of contributions in the literature have 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 USA (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). Digital transformation is the process of using digital technologies to transform existing traditional and non-digital business processes and services, or create new ones, to meet with the evolving market and customer expectations, thus altering the way businesses are managed and operated, how value is delivered to customers, and crucially, how workers are employed in the production process (Majchrzak, Markus and Wareham 2016; Agarwal 2020). This transformation is not limited to technology itself but includes the strategic use of digital tools to reshape business operations, processes, and models, often impacting employees by automating tasks, altering roles, and requiring new skills (Vial 2019). Our perspective on digital transformation thus underscores the evolving demands on workers in adapting to and utilizing these tools within transformed business landscapes.

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 digitalization: two indexes of digitalization in the labour market at the level of industries, and a novel index of digital skills at the individual level. While the indexes capture, by their very nature, only some aspects of the underlying phenomenon, they represent, however, an advance with respect to common analytical approaches that mainly rely on educational attainment to test for the differentiated impact of digitalization on different skill levels. Secondly, we look at a large number of EU countries over a 10 year period (2010–2019), using the largest household survey data available in the European Union (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.[1] This approach, which we refer to as a 'concatenated analysis', involves repeated steps of estimation and simulation, and ultimately enables us to study individual outcomes and determinants of change over a longer period of time than previously possible for specific sub-groups of the population. In conclusion, in our analysis we are able to leverage on the richness of EU-SILC data overcoming its two main shortcomings for the study of the impact of the digital transformation on individuals—without doubt one of the main secular trends transforming labour markets: the lack of measures of digital skills and the short longitudinal dimension of the data. Our findings allow us to support a 'conveyor-belt' hypothesis, indicating that employment provides a competitive edge in managing digital transformation through the learning of relevant skills in the workplace. In our context, the phrase 'conveyor belt' is employed to synthetically and metaphorically illustrate the dynamic trajectory of individuals in employment about the advancement of their digital skills in the workplace. Moreover, it highlights the comparative advantage of the employed over the not employed, emphasizing the potential disadvantage experienced by the latter group. Although a formal 'conveyor belt theory' does not exist in the social sciences, the term has consistently been employed to denote continuous change. Its closest use, also with a similar metaphorical sense, is found in a recent paper in the domain of labour market studies. Moss-Pech (2021) refers to a 'career conveyor belt' for internships and delineates a systematic trajectory linking specific internships to permanent employment opportunities. Internships are frequently linked to prestigious educational establishments and leading corporations, facilitating a rapid pathway for chosen students to obtain employment post-graduation. On the contrary, students lacking such opportunities may endure extended job searches and experience less steady entry into the labour market. These dynamics underscore systemic inequities that influence career paths and long-term job stability among college graduates.

Ultimately, we find that digital skills prove to positively impact the probability of jumping on the conveyor belt for those who are not in employment. In other words, digital skills are relevant for securing employment and attaining higher-paying positions. This also points to the vulnerability of those left behind by the digital transformation and the labour market. Yet the effect of digitalization on labour market outcome depends on individual workers' characteristics, inter alia, the level of formal education. Our findings show that digital skills are more relevant for accessing the labour market and securing better jobs for those with a low or medium level of formal education. This points to a more rapid depreciation of advanced digital skills, as highly educated individuals generally have a more specialized, task-specific type of human capital. Finally, as far as the overall level of income inequality is concerned, we find little evidence of a negative impact of the digital

1 Starting with 2021, the EU-SILC panel design was extended on a voluntary basis to a six-year rotational structure, something we cannot exploit in our analysis.

transformation. The results emphasize, from a policy perspective, the need for up- and re-skilling initiatives, particularly for older individuals.

In this article, we adopt a deterministic view of technological change, treating it as an external factor that drives shifts in productivity, skill requirements, and labour demand, impacting economic outcomes in quantifiable ways. This approach models technological change as a neutral force, separate from social influences or intentions. While we acknowledge the body of literature that views technological change as socially constructed, driven by specific groups' interests and values, examining this process is outside the scope of the article—on this, see for instance Bingham (1996), Wajcman (2002), Olsen and Engen (2007), or Dafoe (2015). Our goal is to assess the economic implications of technology on labour markets and workers, regardless of the social forces shaping it. This deterministic perspective allows us to focus on broad economic trends without delving into their underlying sociological forces. In Section 2, we frame our proposed 'conveyor belt' hypothesis within the existing literature and review the theoretical mechanisms shaping the relationship between the digital transformation and individual employment, wages and inequality, as well as existing empirical evidence. In the rest of the article, Section 3 describes our three indexes of digitalization, the econometric methods, and the concatenated analysis in detail. Section 4 presents estimates of the impact of the various measures of digitalization on employment, earnings, and inequality. Section 5 summarizes 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 and summarizes existing empirical evidence.

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 and Susskind (2018). A significant strand of the literature on the labour market impact of digitalization has focused on estimating 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 USA, 47 per cent of jobs are at high risk of automation (i.e. an automation risk higher than 70 per cent). However, subsequent work stipulated that these numbers likely constitute an overestimation 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 per cent in South Korea to 14 per cent in Austria. Nedelkoska and Quintini (2018) carry out a similar exercise, although they expand the geographical scope of their analysis to include thirty-two countries. They estimate the overall share of workers at a high risk of substitution from automation to be at 14 per cent.

Hence, the overall extent to which jobs are at high risk of automation is uncertain, as well as likely evolving over time and 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 (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, digitalization 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, which in turn, is associated with an 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 linked 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 digitalization, 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.

Whether the displacement effect or compensating mechanisms dominate at the aggregate level is ultimately an empirical question. An increasingly large body of research looks at this question, most commonly investigating the employment impact of technological change on the labour market. The findings of this literature are complex and depend on the level and scope of the analysis (Filippi, Bannò and Trento 2023). Nevertheless, research has increasingly challenged the idea of widespread automation of jobs due to technological change. Hötte, Somers and Theodorakopoulos (2023) conduct a meta-analysis of 127 studies investigating the employment effect of technological change between 1988 and 2021. Across these studies, they find substantially larger support for a labour-creating impact of technological change than a labour-displacing impact, and conclude that, on aggregate, substitution effects of technology appear to be offset by compensating mechanisms. For the European context, a number of recent studies have cast doubt on the notion of a widespread negative employment impact of digitalization (Biagi and Falk 2017; Pantea, Sabadash and Biagi 2017; McGuinness, Pouliakas and Redmond 2023; Bachmann et al. 2024).

As described, the impact of digitalization on workers' employment and wage outcomes is not theoretically clear-cut and depends on the relative importance of displacement effects and countervailing mechanisms. Moreover, these effects are not mutually exclusive and may cancel each other out at aggregate level (Fossen and Sorgner 2022). Based on the findings of the majority of recent empirical studies, we do not expect to find negative effects of digitalization on employment and wages for workers at the aggregate level (Hypothesis 1).

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 the relative demand for higher-skilled workers, leading to improved wage and employment prospects for these workers (Müller 2024). 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 2024). Combined, this should lead to positive employment and wage effects of digitalization 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 sixteen 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 (2016) develop an indicator of routine intensity, aiming to stick as accurately as possible with the theoretical definition, and then run an analysis for twenty-three European countries over the period 1995–2007. Discordant with Goos, Manning and Salomons (2014), they do not find the phenomenon of polarization to be pervasive. On the contrary, they observe that, while polarization seems to be occurring for some countries, 'the most frequent development was in fact one of occupational upgrading', which is more closely aligned with the traditional SBTC hypothesis (Fernández-Macías and Hurley 2016). Similarly, 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 2016; Oesch and Piccitto 2019). Overall, we therefore expect higher-skilled workers to be more likely to benefit from digitalization 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 2016). Hence, we expect negative effects of digitalization 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 (Kristal and Cohen 2016). In this scenario, digitalization is not expected to have effects on inequality at an aggregate level (hypothesis H3b). Unfortunately, directly testing the role of wage-setting institutions is beyond the scope of this article for two main reasons. First, as institutions typically change very slowly over longer periods of time, there would not be enough variation in the data to exploit over the time period under study. Second, we employ a micro-analysis to make good use of the panel data structure of the EU-SILC in order to understand individual level outcomes and conduct a counterfactual analysis to explore how these outcomes may play a role in altering inequality at an aggregate level. Consequently, we would need to change the methodology and our approach to include institutions. Moving forward, this would be an interesting avenue for future research.

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 (Dauth et al. 2021).

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 USA, 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 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 article, we set out to quantify the overall effect of the digital transformation that took place over the decade 2010–9 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, 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. By contrast, EU-LFS has a more limited longitudinal component than EU-SILC, and income information is limited to deciles. 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—that is, the age in the initial period—and 64 is the age the individual is last observed in the sample—that is, 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 where SILC data is only available for Germany from 2018 onwards, which is a period too limited for our analysis.

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 digitalization. In particular, we construct three indexes of digital intensity in the labour market. The first two indexes measure the process of digitalization 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.

3.1.1 Measures of digital transformation at the sectoral level

As highlighted in the previous section, the impact of digitalization 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 investments, in the form of industrial and service robots. The former also covers the increasing role of machine learning algorithms, insofar as they are embedded in software or software services (e.g. online subscriptions). 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.

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.

This database incorporates 'Software and Databases' (labelled as 'Soft_DB') under its intangible assets category. This category is designed to capture expenditures associated with software development and acquisition, as well as database-related investments, including both purchased and internally developed components. Accordingly, it can capture a number of digital innovations that gained widespread adoption in the period 2010–9. Software solutions that would feature therein, and thus in our digital capital intensity index, include, inter alia, cybersecuirty services, Robotic Process Automation (RPA), and Customer Relationship Management (CRM) systems. The index also captures software services powered by Artificial Intelligence (AI) and machine learning algorithms, which in the 2010–2019 period began to influence customer service, predictive analytics, and personalized marketing, though their adoption was less extensive than it is today. Importantly, the scope of Soft_DB aligns with the evolving nature of software delivery models, which increasingly include cloud computing and Software-as-a-Service (SaaS). Specifically, costs associated with SaaS subscriptions, cloud-hosted software platforms, and related services would fall within the category of purchased software. Similarly, expenses for developing proprietary software solutions that leverage cloud infrastructure would be included under the internally developed software component of Soft_DB. By integrating expenditures for both traditional and cloud-driven software solutions, the category ensures comprehensive representation of critical intangible digital investments. Conversely, the index may fail to capture, or capture only to a smaller extent, other transformative processes that took place in this period, such as the precipitous rise of social media platforms, themselves aided by the advent of 4G networks and improvements in mobile technology.

The EUKLEMS & INTANProd 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 Organizations and Bodies) in the NACE2 industry classification. Supplementary Appendix Fig. A1 shows the evolution 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. A robot is defined by the IFR according to the standard classification ISO 8373:2021, as '[an] automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications'. As such, our index can shed considerable light on the extent of automation—that is, a salient aspect of digitalization—in the manufacturing industry. 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. Supplementary Appendix Fig A2 and A3 show 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, urbanization, 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 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 per cent 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 Supplementary Appendix 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).

3.1.2 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 digitalization separately for individuals with low, high and medium levels of education (Low education: ISCED levels 1–2; medium education: ISCED level 3; High education: ISCED levels 4–5), so that heterogeneity in the effects of the measures of the digital transformation can be assessed. 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 twenty-two variables measuring different aspects of digital skills in four categories: information skills; communication skills; problem solving skills; and software skills. The variables included are: 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 software and applications; changing settings of any software; online purchases; 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 organize and analyse data; have written code in a programming language (see Eurostat 2023). 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 per cent 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 variables. The results of the IRT model are shown in Supplementary Appendix 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. The measure is standardized to mean 2 and standard deviation 1, following OECD (2016). Supplementary Appendix Table A2 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 (Supplementary Appendix Table A3) predicting individual levels of digital skill based on individual characteristics (gender, age, employment status, occupation, and education) separately for each year and country. 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. The resulting estimates of levels of digital skills by population characteristics can subsequently be matched to the longitudinal micro-data 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. 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. Models are estimated for each country in isolation and for the EU as a whole, with the exception of Germany, as explained above.

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:

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

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).

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 digitalization (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:

- 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 analysis of employment transitions, all measured in the base year, are: age (second polynomial), sex, education (three levels), region (NUTS-2), degree of urbanization (for most countries: urban, rural, and mixed), occupation (ISCO-08 1-digit classification, only for those starting in employment), and gross earnings quintiles. The degree of urbanization is dropped from the specification for the Netherlands and Slovenia, as the variable is missing for those countries. 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. 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. We use the same covariates of the employment models, but also control for the employment state in the final year, e^{end}:

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

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.

The concatenated analysis therefore involves the following steps:

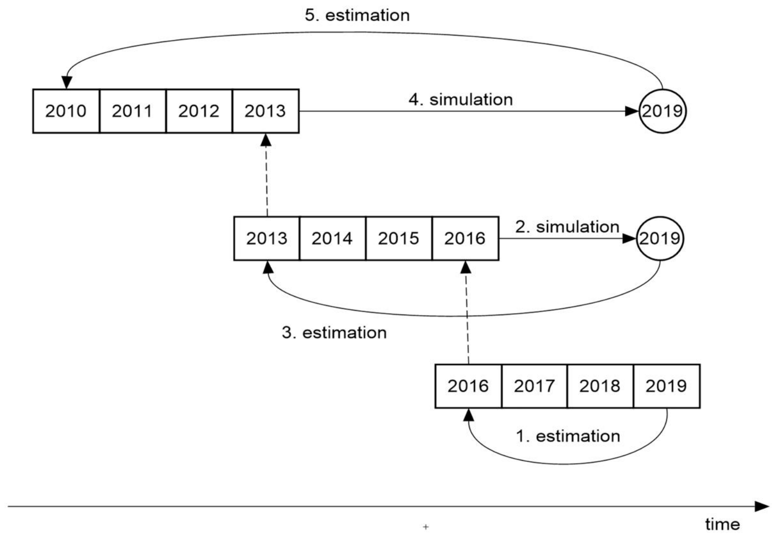

Figure 1. Concatenated analysis.

Notes: Labour market outcomes are estimated using the 2016–9 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 2013–6 wave. Predicted labour market outcomes in 2019 are then related to observed inputs in 2013, using the 2013–6 wave of data. The relationship between 2013 inputs and 2019 (predicted) outputs is then exploited to simulate 2019 outputs for the 2010–3 wave. This allows us to finally relate 2010 inputs to 2019 (predicted) outcomes. We also run analyses on each sub-period (2010–3, 2013–6, and 2016–9) 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.

(1) Estimation of 2019 outcomes (employment and earnings) on 2016–2019 wave.
(2) Prediction of 2019 outcomes on 2013–6 wave, based on the results of Step 1.
(3) Estimation of 2019 (predicted) outcomes on 2013–6 wave.
(4) Prediction of 2019 outcomes on 2010–3 wave, based on the results of Step 3.
(5) Estimation of 2019 (predicted) outcomes on 2010–3 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. 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. Supplementary Appendix B reports the sample for each country and provides descriptive statistics for our estimation sample.

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. 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. 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 twenty-five 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, Supplementary 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 the 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 digitalization, 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.

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.

	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

Notes: 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). Sample: EU27 (excluding Germany).

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

None of the effects are statistically significant, meaning that we find no evidence of either negative or positive 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 line with our first hypothesis, we do not find evidence of a significant negative employment impact of digitalization. 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 digitalization do not appear to affect insiders (i.e. those already in work) much, in terms of their likelihood to remain in employment. Although it is possible that these individuals change job/industry, this is something we cannot check in the data. Details of the country-specific analysis are available on request.

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

The coefficients for the overall population are strongly positive, especially for individuals with a low and medium level of education. In contrast, they are on average not significant 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. 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. The country-specific analysis

Table 2. Estimated coefficients for the effects of the 2010 endowment of digital skills on 2019 employment status.

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

Notes: 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). Sample: EU27 (excluding Germany).
Source: Our computation on longitudinal EU-SILC data 2010–9.

confirms that this pattern is of 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 (Fig. 2). In addition, 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

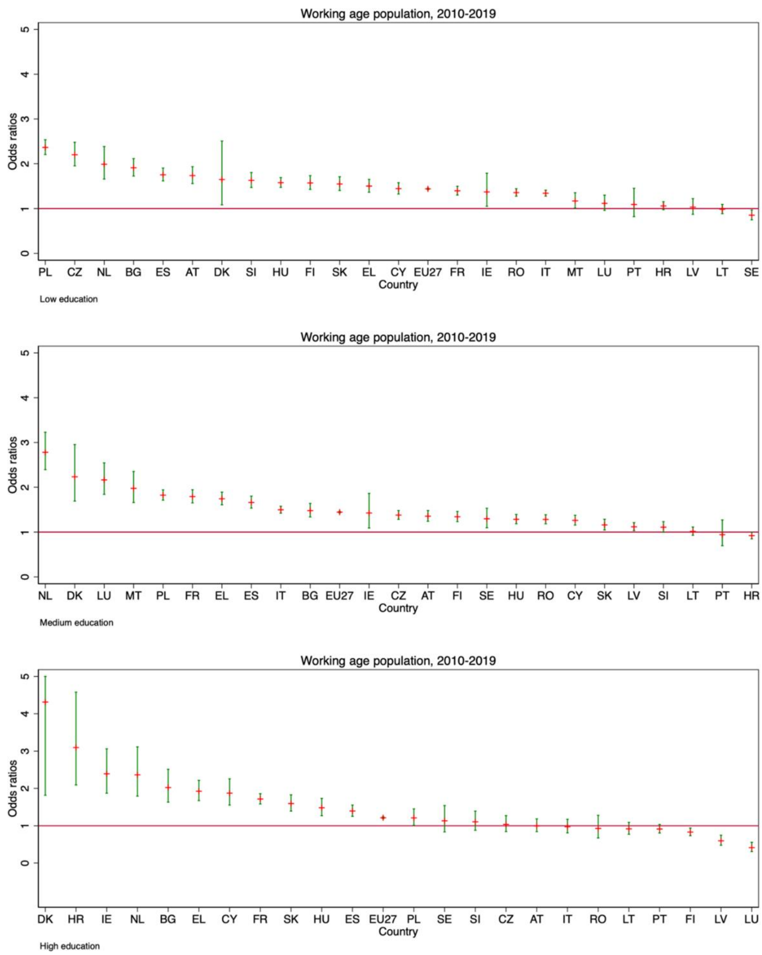

Figure 2. Effects of digital skills endowment in 2010 on the probability of being employed in 2019 (odds ratio) by education attainment level, all individuals aged seventeen to fifty-five in 2010.

Notes: EU27 is excluding DE. The figures report boxplots 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 2010–9.

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—that is, 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 heterogeneity 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 Supplementary Appendix 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 a hypothesis that we advance based on our empirical results, but that would require 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.

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 (details of the country-specific analysis are available on request). Hence, as in the case of employment, we do not find evidence of either a negative or

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.

	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

Notes: 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. Sample: EU27 (excluding Germany).
Source: Our computation on longitudinal EU-SILC data 2010–9.

Table 4. Estimated coefficients for the effects of the 2010 endowment of digital skills on gross earnings growth between 2010 and 2019.

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

Notes: 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. Sample: EU27 (excluding Germany).
Source: Our computation on longitudinal EU-SILC data 2010–9.

positive effect of various types of digitalization at sectoral level on individual earnings outcomes, for both net and gross earnings.

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).

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 unionized). 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 Supplementary 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 per cent for a large increase in digital skills (one standard deviation) over a relatively 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 and details of the country-specific analysis are available on request.

4.3 Effects on inequality

To evaluate the effects on inequality, we employ a 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

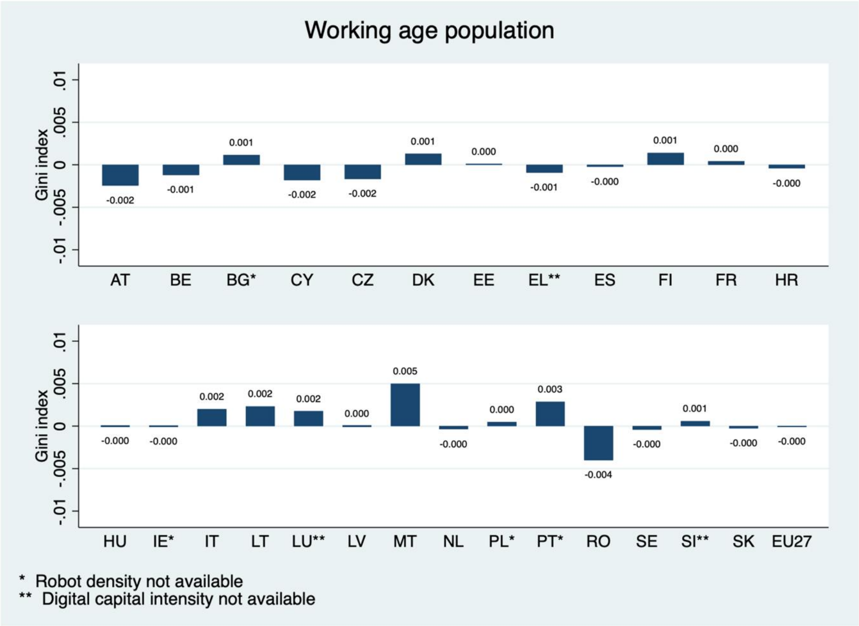

Figure 3. Impact of digital transformation on gross income inequality (Gini coefficient), 2010–9.
Source: Our computation on longitudinal EU-SILC data 2010–9.

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.

5. Discussion

Apart from the effects on employment, which support our 'conveyor belt hypothesis', few 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 digitalization has no effects on labour markets. Rather, as highlighted in the review of theory, the effects of digitalization 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 of digital transformation, like the ability of new technologies to perform tasks previously undertaken by humans, may be offset by countervailing mechanisms such as productivity effects or the creation of new tasks, 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 national level of inquiry.

Productivity effects refer to increases in labor demand for non-automated tasks, occurring both in sectors undergoing automation and in unaffected sectors. These effects operate through two key channels: the price-productivity effect, where automation reduces costs, leading to lower prices, expanded sales, and increased hiring; and the scale-productivity effect, where widespread price reductions boost local economies, creating spillover demand for labor in adjacent industries. Additionally, digitalization drives the creation of new tasks, which may lead to employment and wage gains. These tasks could be more complex versions of existing activities or entirely new roles, often complementing technology. In such cases, workers may have a comparative advantage over machines, contributing to a reinstatement effect that mitigates job displacement—though the extent of this offset depends on factors such as skill adaptability and retraining opportunities.

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 do 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 prolonged 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 localized and temporaneous adverse effects: at the national level and over extended periods, the negative impacts of digital transformation may be less severe than expected, highlighting the adaptability of EU labor markets.

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 USA) or time periods (e.g. 1990–2010). The 2010s have experienced relatively stable advancements in existing digital technologies, as opposed to the emergence of new paradigms that dramatically disrupted labour markets. For instance, significant digital developments of the decade such as advancements in cloud computing, big data analytics and the mobile internet 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 can be argued to have further increased globalization and outsourcing. This is 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 AI and the impending new wave of transformation. This is largely because the real-world implementation of AI across various industries remained tentative and experimental during the 2010s, despite significant speculation about its potential impact. However, with the recent rapid expansion of applied AI 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. 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 of the new production processes by domestic firms 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 subperiods, 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 labour market during the 2010s, the results do suggest an important finding: digital skills are crucial to finding a job, yet less so for retaining one. What we denote 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 work, 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. 70 per cent of 25–34 year olds have basic or above average overall digital skills, reducing to 44 per cent of 55–64 year olds (Eurostat 2023). 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 per cent of adult participation in annual training by 2030. While progress is being made—43.7 per cent in 2016 to 46.6 per cent in 2022 (Eurostat 2023)—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 developments.

Supplementary data

Supplementary data is available at *Socio-Economic Review Journal* online.

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