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# Governing the Digital Transition: The Moderating Effect of Unemployment Benefits on Technology-Induced Employment Outcomes

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## Abstract

The digital transition shapes work in numerous ways. For instance, by affecting employment structures. To ensure that the digital transition results in better employment opportunities in terms of socio-economic status, labour markets have to be guided appropriately. The European Pillar of Social Rights can be the political framework to foster access to employment and tackle inequalities that result from the digital transition. Current research primarily examines scenarios of occupational upgrading and employment polarisation. In the empirical literature, there is no consensus on which of these developments prevail. Findings vary between countries and across different study periods. Accordingly, this article provides a theoretical explanation for the conditions under which occupational upgrading and employment polarisation become more likely. Further, this article examines how the use of information and communication technology (ICT) capital in the production of goods and services affects the socio-economic status of individuals and, more importantly, whether unemployment benefits moderate this effect. Methodologically, the article uses multilevel maximum likelihood regression models with an empirical focus on 12 European countries and 19 industries. The analysis is based on data from the European Labour Force Survey (EU-LFS), the European Union Level Analysis of Capital, Labour, Energy, Materials, and Service Inputs (EU-KLEMS) research project, and the Comparative Welfare Entitlements Project (CWEP). The results of the article indicate that generous unemployment benefits are associated with occupational upgrading. This implies that educational and vocational labour market policies need to be developed to prevent the under-skilled from being left behind and to enable these groups to benefit from the digital transition. Consequently, it is not only the extent to which work involves routine tasks or the skills of workers that determine how technological change affects employment, but also social rights shape employment through unemployment benefits.

**Keywords**
digitalisation; employment; employment polarisation; labour markets; occupational upgrading; social rights; unemployment benefits

## 1. Introduction

The digital transition has a substantial impact on employment (Balsmeier & Woerter, 2019); in particular, it poses a major threat to fair working conditions, the second dimension of the European Pillar of Social Rights (EPSR). Important headline indicators of this dimension are employment and unemployment rates. The extent to which the digital transition leads to changes in employment and unemployment has distributional implications. This is the case because equality of opportunity in the labour market can be reduced for people with low(er) levels of qualifications, and because labour markets and welfare states are important factors for social stratification (Esping-Andersen, 1990). There is a risk that under-skilled citizens are being left behind, further aggravating existing inequality, hampering their social participation, or reducing socio-economic status (SES) for lower- and—potentially—medium-SES individuals. Against this background, the present article touches on issues of distributive fairness arising from changes in the employment structure. It addresses how labour markets can be guided in the right direction to ensure social inclusion and fair employment opportunities during and in spite of the upheavals caused by the digital transition.

Overall, the digital transition is expected to shape labour markets by affecting job creation and destruction. In their seminal paper, Frey and Osborne (2017) conclude that through the digital transition it is likely that 47% of occupations are potentially automatable through computerisation in the US. However, others, such as Arntz et al. (2017), conclude that this scenario overstates the automatability of jobs, as there is substantial task heterogeneity within occupations. When this task heterogeneity is considered, the authors conclude that the automatization risk drops to only 9% of jobs.

Fears of technological unemployment are not new, but current hypotheses about how the digital transition will affect employment suggest that while jobs will change, work itself is unlikely to end. Evidence from socio-economic literature indicates that, overall, technological change does not destroy more jobs than it replaces (Autor, 2015; Cords & Prettner, 2022; Gartner et al., 2019). In this sense, the scenarios of occupational upgrading and employment polarisation propose two different scenarios for the future of employment and its implications for fair working conditions. Both scenarios describe how the distribution of jobs could change due to digitalisation and imply that the impact of new technologies on employment will differ for different kinds of workers.

Occupational upgrading or the skill-biased technological change (SBTC) hypothesis predicts disproportionate employment growth in better-paid and higher-skilled occupations at the expense of lower-paid and lower-skilled occupations (Card & DiNardo, 2002; Fernández-Macías & Hurley, 2017). The underlying assumption is that information and communication technology (ICT) is skill-biased, which assumes that ICT increases the relative productivity of high-skilled workers, who tend to be better at using new technologies. Consequently, job creation tends to focus on better-skilled workers, as demand for such workers rises with their increase in productivity. Changes in the employment structure are therefore driven by the skill requirements of jobs (Mondolo, 2022).

Employment polarisation or the routine-biased technological change (RBTC) hypothesis states that job growth takes place for high-paid and low-paid occupations but decreases for medium-paid occupations (Autor, 2015; Fernández-Macías & Hurley, 2017; Goos & Manning, 2007). This hypothesis assumes that job tasks can be divided inter alia into routine and non-routine tasks. According to the RBTC hypothesis, medium-skilled jobs disappear relatively to lower- and higher-skilled jobs because those jobs contain more routine tasks. For this reason, digitalisation is assumed to be routine-biased, meaning that labour-intensive routine tasks can be more easily replaced by digitalisation. This is the case as with technological improvements and decreasing prices for computer capital over time, ICT becomes relatively cheaper in comparison to repetitive labour (Mondolo, 2022; Sebastian & Biagi, 2018). Thus, ICT is not considered to be an adequate substitute for non-routine tasks.

While both scenarios differ in their predictions regarding the effect of the digital transition on employment, they also differ regarding their effects on social inclusion and fair working conditions. On the one hand, occupational upgrading could lead to an overall increase in SES among the employed, but at the expense of less labour market participation or unemployment of lower-skilled workers. On the other hand, employment polarisation could lead to more inequality as medium-skilled and routine-intensive jobs are substituted by digital technologies, while ensuring the labour market participation of lower-skilled workers. In any case, both scenarios require social policy measures if the employment structure changes, and certain jobs become relatively less existent. For instance, educational and vocational labour market policies targeted at those adversely affected by the digital transition may be necessary to ensure their social participation and prevent a decline in their SES. This is also relevant from a societal perspective as a low SES is associated with negative effects on health outcomes (Evans & Kim, 2010; McMaughan et al., 2020), lifetime pensions (Shi & Kolk, 2023), the likelihood of criminal behaviour (Baker et al., 2023), or reduced political participation (Nelson, 2023). Consequently, it is essential to understand how employment changes.

The goal of the EPSR to provide good employment with fair working conditions is therefore contingent upon the analysis of how job creation can be influenced and how welfare states adapt to changes in labour demand for worse-off workers. Fostering a scenario of occupational upgrading aligned with upskilling of workers could ensure that fewer individuals are left behind. This is especially the case as the labour market is for work-dependent individuals the main allocator of SES in market-based economies.

Research on the technology–employment nexus examining the role of labour market institutions has mainly focused on the role of unions (Haapanala et al., 2023; Kristal & Cohen, 2017). Focusing empirically on unemployment benefits provides new insights, as unemployment benefits consider individuals independently of union membership. Further, unemployment benefits can be more easily governed by the state than union behaviour in bargaining processes.

This article investigates the extent to which the generosity of unemployment benefits moderates the relationship between ICT capital and employment. Further, it addresses the question of why heterogeneous results on occupational upgrading and employment polarisation are reported, and consequently explains under which conditions one or the other is more likely to occur. The central argument is that unemployment benefits, as a part of social rights, moderate the effect of ICT capital on employment and respectively SES. This is the case because these benefits affect the labour market behaviour of employers and employees.

The contribution of this article is threefold: First, it offers a theoretical explanation for why empirically occupational upgrading and employment polarisation are observable. Second, by focusing on unemployment benefits, it extends the literature on the role of institutions in the relationship between employment and technology. Third, the use of multilevel models broadens the methodological scope. To the best of my knowledge, such models have not been employed to examine the relationship between ICT capital and SES subgroups measured by International Socio-Economic Index of Occupational Status (ISEI-08) scores. Moreover, it uses time-varying indicators for labour market institutions in this relationship. This article extends the literature as it measures employment with ISEI-08 scores. For instance, previous papers have considered prestige scales (Ulfsdotter Eriksson et al., 2022). While prestige scales and ISEI-08 scores are related, they measure different things. Prestige scores are measures for the popularity of an occupation and the ISEI-08 score measures the cultural and economic resources that are typical for incumbents of a certain occupation (Ganzeboom et al., 1992).

The article is structured as follows: The next section provides an overview of the literature related to this article. Section 3 presents the research question and develops the argument, followed by the presentation of the hypotheses. Sections 4 and 5 describe the data and the empirical strategy. Section 6 presents the results. The article concludes with Section 7, which provides a discussion and a conclusion.

## 2. Related Literature

The contribution of this article is related to the literature on the effects of technology on employment, with particular focus on the role of labour market institutions in this process. The article starts with the observation that the literature comes to different conclusions about whether occupational upgrading or employment polarisation has taken place, depending on the selected countries and time spans. Based on these heterogeneous results, this article examines whether unemployment benefits as labour market institutions (Checchi & García-Peñalosa, 2008) influence the conditions under which employment polarisation or occupational upgrading occur. For a systematic literature review on the link between technology and employment, consider Mondolo (2022). The literature review indicates that technology affects employment outcomes and that there are various theories and mechanisms that explain this relationship. However, it also states that the evidence for which theory or mechanism is correct is inconclusive, also depending on the unit of analysis. Further, Mondolo (2022) states that labour market institutions can be moderators in the relationship between technological change and employment. Oesch (2013, p. 110) argues this is the case because labour market institutions determine the wage floor and influence whether low-skilled jobs increase in number.

On the one hand, evidence that RBTC leads to employment polarisation can be found in several articles. Initially, the argument that technology increases job growth at the margins of the employment distribution was proposed by Autor et al. (2003). In their study, the authors find that computerisation is associated with less labour input of routine-manual and routine-cognitive tasks while increasing labour input of non-routine cognitive tasks in the US. Further, Goos and Manning (2007) find that from the 1970s to the 1990s a pattern of job polarisation is observable in Britain. This evidence was further supported by Goos et al. (2014) who show that job polarisation within and between industries is present in 16 European countries in the period of 1993–2010. Moreover, Michaels et al. (2014) find evidence for employment polarisation due to ICT use in nine European countries, the US, and Japan from 1980 to 2004. Finally, Fonseca et al. (2018) use firm census data to report for Portugal that they find employment polarisation in the second half of the period of 1986–2007 in terms of wages and employment.

On the other hand, there is literature contesting the claim of employment polarisation. Oesch and Rodriguez Menes (2011) find evidence for occupational upgrading in the period of 1990–2008 in Britain, Germany, Spain, and Switzerland. Moreover, Oesch and Piccitto (2019) state that employment polarisation is rather a myth as they find again clear evidence for occupational upgrading in Germany, Spain, and Sweden, and partial evidence for occupational upgrading in the United Kingdom during the time span of 1992–2015. Further, Ulfsdotter Eriksson et al. (2022) find in their gender-based analysis evidence for occupational upgrading for women but employment polarisation for men in Sweden from 1997 to 2005. In a similar direction, Murphy and Oesch (2018) find evidence for occupational upgrading that is driven by higher educated women in Ireland and Switzerland from 1970 to 2010. Lastly, Alasoini and Tuomivaara (2023) provide evidence that employment polarisation does not hold in Finland from 2013 to 2018.

Another strand of literature relevant to this article considers the role of other labour market institutions, such as unions, in the relationship between technology and employment. Kristal and Cohen (2017) find in their article that rising wage inequality in the US—typically associated with occupational upgrading—is rather explained by a decline in union strength and the reduced real value of minimum income than by the computerisation of workplaces. Haapanala et al. (2023) discuss in their study the moderating effect of union density on technological unemployment in 27 European countries and the US from 1998 to 2019. They conclude that higher union density goes hand in hand with a larger reduction in industry-sector employment for younger workers and workers with lower secondary education in the case of more robot use. Further, they find that in countries with low union density, the unemployment rate falls more strongly as robot exposure increases. This result allows the conclusion that technological change is not beneficial for all types of workers to the same extent.

Despite unions representing a pivotal institution to express workers' interests and organizing bargaining power, they suffer from an insider–outsider problem, meaning that their effect could be limited to the workers the corresponding union is representing (Jansen & Lehr, 2022; Lindbeck & Snower, 2001). Further, union density declined in the last decades, leading to a weaker representation of workers' interests in many European countries (Vachon et al., 2016). This implies that it may not be sufficient to consider trade unions alone when assessing the role of labour market institutions in the employment–technology nexus. Accordingly, this article examines whether other labour market institutions, like unemployment benefits, have a moderating effect on technology-induced employment outcomes.

In a similar direction, Fernández-Macías (2012) presents evidence for both employment polarisation and occupational upgrading in Europe. This can be explained via labour market institutions, as they shape the allocation of labour through regulations such as minimum income, health regulations, and unemployment protection. Fernández-Macías (2012) concludes that changes in employment patterns coincide with institutional clusters like Continental, Scandinavian, and Southern Europe. Other literature related to institutions, such as Oesch (2015), argues that welfare-state regimes also play an important role in technological unemployment. The article suggests that there is evidence of clear occupational upgrading in Denmark and Germany, with a more polarised version of upgrading in Britain, due to the expansion of high- and low-end service jobs. Oesch (2015) states that these results are explained through an interaction between welfare regimes and labour supply that drives these employment changes. It is assumed that welfare states shape employment creation and social classes, as argued by Esping-Andersen in *Three Worlds of Welfare Capitalism* (1990). The current article builds on the argument put forward by Oesch (2015).

This article emphasises that it is especially the generosity of unemployment benefits that affects labour demand and supply. As welfare regimes are rather static concepts, this article uses time-varying indicators like the generosity of unemployment benefits as part of social rights. In accordance with Kunißen (2023), it is assumed that although welfare states are an important variable in explaining how technology affects employment, it is more accurate to focus on single indicators. The reason why single indicators are more precise than welfare regimes is that they allow us to specify which aspects of welfare states lead to a certain result. Thus, the interpretation that welfare states influence an outcome lacks clarity. To be more exact, it is necessary to find answers to why welfare states can explain variance and how explanatory mechanisms work (Kunißen, 2023, p. 68).

Considering these heterogeneous results, this article contributes to the ongoing puzzle of why employment polarisation and occupational upgrading are observable and elaborates on the conditions that make one or the other more likely to occur. The central argument of this article is in line with other authors that state labour market institutions like unions or welfare states are relevant factors in explaining the effect of technology on employment. However, this article makes a novel contribution by arguing that the generosity of unemployment benefits as part of social rights is an important variable for assessing the impact of technology on employment.

## 3. Research Questions, Argument, and Hypotheses

Based on the literature, the two research questions of this article are:

1. Why do we empirically observe occupational upgrading in some countries' labour markets, while we see employment polarisation in others?
2. To what extent does the generosity of unemployment benefits moderate the relationship between the use of ICT capital in the production of goods and services and labour market outcome measured by ISEI-08 scores during the period 1998–2019?

To explain the heterogeneous findings in the literature, I argue that it is not only the extent to which work contains routine tasks, or the workers' skill set, that determine how technological change affects employment, but also the institutional setting shapes employment patterns through social rights. Following Marshall (1950, p. 11), social rights, as a part of social citizenship, can be described as access to a minimum level of economic protection in relation to a given society's living standard. Because capitalist society is based on inequality of opportunity, wealth, and income, Marshall states that social rights become necessary to maintain democratic principles of equality (Turner, 2001, p. 190).

Based on Marshall's understanding and in line with Esping-Andersen (1990), in this article it is assumed that unemployment benefits are part of social rights as they de-commodify workers and therefore provide the means to live independently of work while receiving these benefits. One could argue that social rights can be considered as an equivalent to possessing means of production, as they enable an existence independent of wage labour. In other words, unemployment benefits are part of social rights as they make individuals less dependent on market incomes. However, it should be noted that unemployment benefits only de-commodify workers if they are covered, they fulfil the eligibility criteria, and they take up the benefits.

Unemployment benefits as part of social rights explain variation in technology-induced employment outcomes because they affect the labour market behaviour of individuals and companies. Individuals' motivation to participate in the labour market consists of obtaining economic resources and fulfilling their job preferences given their set of individual restrictions. The motivation for companies to create jobs is to maximise profits by optimising inputs such as capital and labour. Unemployment benefits influence job creation because (a) they protect workers from selling their labour to the first best job they find and are in that sense a job-search subsidy—Gangl (2006) and Biegert (2017) provide evidence that unemployment benefits reduce job mobility into the low-skill sector and reduce unemployment through better job matching—and (b) they influence the minimum standards and reservation wages that companies must meet or exceed to hire workers, as argued by Marinescu and Skandalis (2021). Although job search models imply that higher reservation wages lead to more unemployment, higher reservation wages could also increase the quality of the remaining jobs in terms of SES. In accordance with this claim, Nekoei and Weber (2017) find that extending the duration of unemployment insurance leads workers to find jobs that pay higher wages. In sum, unemployment benefits could influence job creation as they make labour supply relatively more expensive in relation to capital use and consequently affect a firm's incentives to replace labour with ICT capital. As a result, unemployment benefits as part of social rights do not only allow individuals to be less work-dependent but also have an impact on labour demand and supply.

If unemployment benefits protect workers from selling their labour to employment opportunities that lead to low pay, insecure employment, or low SES, companies will have to respond as their demand for such labour will not be met. In that sense, unemployment benefits can be understood as a job search subsidy, as they reduce the individual need to accept the first best job they find. Consequently, companies will instead seek to create jobs that lead to higher SES to incentivise workers to work for them, as the workers' reservation wages increase with more generous unemployment benefits. Additionally, if the use of ICT capital leads to higher productivity gains for better-skilled workers, there are additional incentives to create higher SES jobs. Overall, this leads to occupational upgrading, as jobs associated with low SES are replaced by medium and high SES jobs. I thus hypothesize:

> H1: More generous unemployment benefits are associated with occupational upgrading in the relationship of ICT-capital use and ISEI-08 scores, ceteris paribus.

If unemployment benefits offer insufficient protection to workers, they are more likely to sell their labour to the first best job they can find. Companies have less incentive to create jobs that lead to higher SES, as workers have lower reservation wages and are therefore more easily available for lower SES jobs. Hence, firms create jobs with low SES because it is relatively cheaper to use labour than ICT capital as workers are more easily available for low SES jobs. If the use of ICT capital is routine-biased, then in the absence of generous unemployment benefits, companies have even fewer incentives to create medium-skilled jobs. In sum, this leads to employment polarisation because the absence of generous unemployment benefits fosters further polarisation. Hence, I hypothesize:

> H2: Less generous unemployment benefits are associated with employment polarisation in the relationship of ICT-capital use and ISEI-08 scores, ceteris paribus.

## 4. Data

This article examines whether the effect of ICT capital on SES for different SES subgroups is moderated by the generosity of unemployment benefits and whether the results indicate that occupational upgrading or employment polarisation is more likely. The analysis is based on 12 countries (Austria, Belgium, Denmark, Germany, Greece, Finland, France, Italy, the Netherlands, Spain, Sweden, and the UK) and 19 NACE Rev. 2 industries (A–S) in the time span of 1998–2019. The NACE Rev. 2 industries T (activities of households as employers) and U (activities of extraterritorial organisations) are not included because there is no data on ICT capital for these industries available in the European Union Level Analysis of Capital, Labour, Energy, Materials, and Service Inputs (EU-KLEMS) data. The analysis is restricted to persons who are employed and belong to the working population aged 18–65. Four data sources were used to account for all needed variables.

First, measures for individual SES and the corresponding covariates are obtained from the European Labour Force Survey (EU-LFS) provided by Eurostat (2024). The data contain information on all national labour markets in the EU and are used to estimate key labour market metrics for each member state. As the target population of this article is the working population, the data are suitable for this analysis. EU-LFS includes information on the main job of the respondent based on International Standard Classification of Occupations (ISCO) codes. Depending on the year of the survey (prior to or after 2008), these codes are coded as three-digit ISCO-08 or ISCO-88 codes. Further, the codes were used to derive the ISEI-08 score for each respondent with the Stata user-written command *iscogen* (Jann, 2019). Therefore, the main dependent variable in the analysis is the respondent's ISEI-08 score.

The ISEI-08 score ranks occupations based on corresponding values for income earned and education required to be employed in a certain occupation (Ganzeboom, 2010). It measures the attributes of occupations that translate an individual's education into income by maximizing the indirect effect of education on income and minimizing the direct effect (Ganzeboom et al., 1992). The ISEI-08 score is derived from ISCO codes and is based on data from 200,000 cases, covering information on education, occupation, and personal income in 42 countries (Ganzeboom, 2010). The index attributes a scale on a range from 10 to 90 and is a continuous measure for the SES of an individual. The main reason for using ISEI-08 scores as the main dependent variable is that it allows to a greater extent to account for the variability in SES between occupations.

Second, the Comparative Welfare Entitlements Project (CWEP) dataset was used to obtain measures for the generosity of social rights regarding unemployment benefits (Scruggs, 2022). This dataset offers quantitative information on the development of welfare institutions in 33 democracies around the world (Scruggs & Ramalho Tafoya, 2022). The data focus on the non-spending features of major public social insurance and calculate the generosity of welfare programs. The data source is used as it aims to replicate Esping-Andersen's (1990) *Three Worlds of Welfare Capitalism*'s decommodification index and can be understood as an update for social citizenship indicators, measuring the generosity of unemployment insurance as part of social rights (Scruggs & Ramalho Tafoya, 2022). Further, the CWEP data allow international comparison and consider that welfare generosity can vary over time. Since the article argues that the generosity of unemployment benefits is an important institutional factor in the labour market behaviour of work-dependent individuals and firms, the data are appropriate to answer the research questions. The unemployment generosity index for each country and year is based on the following intuitive criteria of the benefit: (a) the replacement rates, (b) the duration of benefits receipt, (c) the needed qualifying period, (d) the waiting days to receive the benefit, and lastly (e) the benefit coverage. Based on these criteria, a welfare generosity score is composed by creating a z-score for each characteristic using the mean and standard deviation by country and year. The index for the selected countries ranges from 3.75 to 15.27. Figure 1 shows the development in generosity of the unemployment benefits over time for the considered countries, where changes within welfare states become evident.

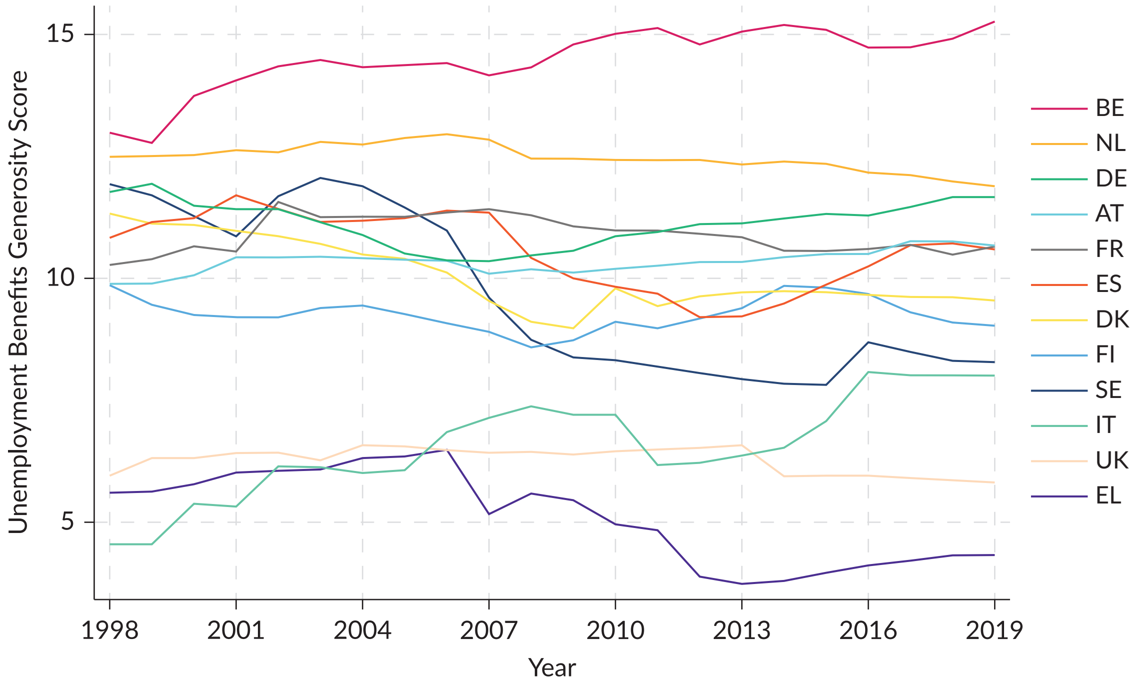


**Figure 1.** Unemployment benefits generosity scores from 1998 to 2019 in the countries under consideration. Source: Author's own illustration based on CWEP data.

Third, the statistical module on capital accounts from the EU-KLEMS (release 2023) data was applied to measure the use of ICT capital in the production of goods and services in 19 different NACE Rev. 2 industries. EU-KLEMS data are collected from EU countries and provide detailed information on a range of economic indicators, including growth, productivity, employment creation, capital formation, and technological change at the industry level for all EU member states (Bontadini et al., 2023). The data are used to derive a proxy variable for ICT capital that measures approximately the extent to which different industries in different countries use ICT to produce goods and services. This variable is created as proposed by Gschwent et al. (2023), where ICT capital is based on tangible and intangible assets, namely (a) computer hardware (tangible), (b) telecom equipment (tangible), and (c) computer software and databases (intangible). To obtain the ICT-capital indicator, a new variable was created by adding the three assets. Each asset is measured as the net worth of the capital stock, in millions of national currencies, which are harmonized across countries. In the next step, the ICT-capital stock was divided by the value of all other assets that are used in the production of goods and services and the result was multiplied by 100. This was done to obtain a measure that shows the percentage of all assets within an industry that can be classified as ICT capital. As the analysis relies on cross-sectional data, the chained volume series based on the 2015 values is used to account for price changes over time. Figure 2 illustrates differences in capital use over time for the NACE industries considered. The figure indicates that the NACE Rev. 2 industries J (information and communication), K (financial and insurance activities), and M (professional, scientific, and technical activities) are the industries with the highest share of ICT-capital use in 2019. Further, the graph shows that the use of ICT capital varies considerably among industries over time.

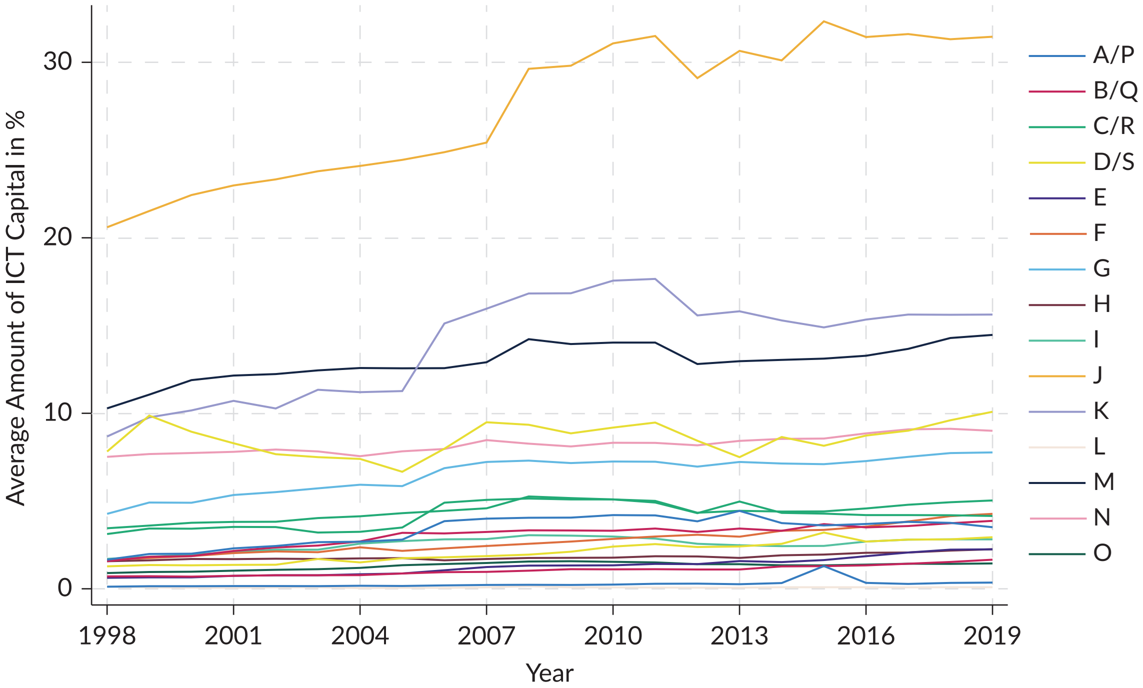


**Figure 2.** Average amount of ICT capital in NACE Rev. 2 industries as a percentage of all assets in all considered countries from 1998 to 2019. Notes: Letters are abbreviations for the following industries: A (agriculture, forestry and fishing), B (mining and quarrying), C (manufacturing), D (electricity, gas, steam and air conditioning supply), E (water supply; sewerage, waste management and remediation activities), F (construction), G (wholesale and retail trade; repair of motor vehicles and motorcycles), H (transportation and storage), I (accommodation and food service activities), J (information and communication), K (financial and insurance activities), L (real estate activities), M (professional, scientific and technical activities), N (administrative and support service activities), O (public administration and defence; compulsory social security), P (education), Q (human health and social work activities), R (arts, entertainment and recreation), S (other service activities). Source: Author's own illustration based on EU KLEMS data.

Finally, OECD data are used to obtain variables that consider a country's real economic growth and GDP per capita. The model controls for economic growth, as the investment decisions of private and public firms in ICT capital may be different during economic crises than in boom years. If less economic growth reduces investments in ICT capital, this could confound the relationship between digital capital, unemployment benefits, and SES. Additionally, the full model controls for GDP per capita as the effect of ICT capital on SES might differ depending on a country's prosperity. Therefore, the variables "annual real GDP growth" and "GDP per capita in US dollars per person, PPP converted at current prices" are added from the OECD data (OECD, 2024a, 2024b).

## 5. Empirical Strategy

In a first step, I compare the cumulative distribution functions of ISEI-08 scores in 1998 and 2019 to check for employment shifts between these two points in time. Next, I calculate regression models to account for the specific effects of unemployment benefits and ICT capital on SES for different subgroups. To be more precise, the article applies linear multilevel maximum likelihood regression models with random intercepts. Due to the theoretical assumption that there is dependence of observations between individuals who work in the same country and industry, the article assumes a nested data structure. Further, from a theoretical perspective, it is not expected that the magnitude and direction of the effects of unemployment benefits differ between country-specific industries. This is the case as the analysis assumes that the protecting effect of generous unemployment benefits is equal among the considered clusters. Therefore, multilevel models with random intercepts are reasonable for this analysis. The complete model looks as follows:

$$\begin{aligned}\text{ISEI Score}_{ij} = {} & \beta_0 + \beta_1\text{Sex}_{ij} + \beta_2\text{Age}_{ij} + \beta_3\text{Urbanisation}_{ij} + \beta_4\text{Citizenship}_{ij} + \beta_5\text{Education}_{ij} \\ & + \beta_6\text{Part Time Work}_{ij} + \gamma_1\text{Unemployment Generosity}_j + \gamma_2\text{ICT Capital}_j \\ & + \gamma_3(\text{Unemplyoment Generosity} \times \text{ICT Capital})_j + \gamma_4\text{Real GDP Growth}_j \\ & + \gamma_5\text{GDP per capita}_j + \varepsilon_{ij} + U_{oj}\end{aligned}$$

In this regression equation, $i$ indicates the individual respondent and $j$ the country-specific NACE Rev 2. industry, $\beta_0$ stands for the country-specific intercept, $\varepsilon_{ij}$ represents the individual-level error term, $U_{oj}$ represents unobserved country effects, $\beta_n$ represents the regression coefficients of the corresponding covariates, and $\gamma_n$ represents the regression coefficient of the corresponding level-two variable. All calculations were performed using Stata version 18.5.

The model predicts an individual's SES based on ISEI-08 scores. Further, the model controls on the individual level for the respondent's sex, age, degree of urbanisation in place of residency, citizenship, educational level, and if the respondent is part-time employed. These variables are selected because the literature indicates that (a) women work more often in occupations that lead to lower pay than men (Manning & Petrongolo, 2008), (b) income changes during the life course (Toczek et al., 2021), (c) better-paid jobs demanding more skills are concentrated in urban areas (Rouwendal & Koster, 2025), (d) non-natives tend to work in lower SES occupations (Fullin & Reyneri, 2011), (e) higher education enables access to higher SES jobs (Ganzeboom et al., 1992), and (f) part-time workers tend to suffer from part-time penalties in terms of income or promotions (Bardasi & Gornick, 2008; Deschacht, 2017). The main explanatory variables, the generosity of unemployment benefits and the amount of ICT capital, are found on the second level. No problematic correlation between the independent variables is found.

Sex is coded as a dummy variable, taking the value 1 if the respondent is female. Age is a continuous variable ranging from 18 to 65 years. However, it should be noted that in the Dutch EU-LFS data, age is reported only in categories. To overcome the problem of different scales for the age variable, the midpoint of each Dutch age category is combined with the single-year age variable. The urbanisation variable indicates whether the respondent lives in a city, town or suburb, or in a rural area, the latter being the reference category. Citizenship is a dummy variable indicating whether the respondent holds a foreign passport. The education variable indicates the respondent's highest educational attainment and distinguishes whether the respondent completed tertiary, upper-secondary, or lower-secondary education, with lower-secondary being the reference category. Lastly, the part-time work dummy variable indicates whether the respondent is employed part-time.

From a theoretical perspective, RBTC and SBTC make different predictions about the impact of ICT capital on the employment structure. Therefore, the original sample is divided into three terciles of respondents with low ($x \leq 34$), medium ($34 < x \leq 49$), and high ($x \geq 50$) ISEI-08 scores. The division allows us to examine if the effect of the main independent variables varies across socio-economic groups. If digital technologies do not favour all groups to the same extent, then we should observe effect heterogeneity of ICT capital across these groups. In the case of occupational upgrading, the results should suggest that ICT capital increases ISEI-08 scores across all subgroups. In contrast, the scenario of employment polarisation would imply that ICT capital increases ISEI-08 scores of individuals in the high SES group and decrease ISEI-08 scores of individuals in the medium and low SES groups.

As stated, I assume a nested data structure consisting of two levels. Country-specific industries are created by grouping country with NACE Rev. 2 identifier variables. Due to changes in the NACE classifications in 2008, NACE Rev. 1 classifications are converted into NACE Rev. 2 classifications for observations prior to 2008 by using a crosswalk table. The table is manually created and is based on a correspondence table provided by the European Commission (2008, p. 47). However, as the industry structure changes over time and new industries emerge, it is not possible to convert all NACE Rev. 1 into NACE Rev. 2 classifications. To check whether the analysis is sensitive to changes in the NACE classification, I repeat the analysis only for the period between 2008 and 2019, where no conversion of classifications is necessary. By using a subset of the data, the results show that they are not sensitive to the conversion. Hence, in sum, the analysis is based on 12 countries and 19 NACE Rev. 2 industries which leads to 228 ($12 \times 19$) country-specific industries. The literature indicates no clear evidence on the number of clusters needed for reliable estimates when computing multilevel models. However, using Monte Carlo simulation, Bryan and Jenkins (2016, p. 19) show for linear models that at least 25 clusters are required to ensure the validity of the results.

## 6. Results

Figure 3 shows descriptively the cumulative distribution of ISEI-08 scores in 1998 and 2019. Overall, the graph indicates a right shift of the distribution, especially for individuals of medium and high SES. This indicates that in comparison to 1998, there is a trend of occupational upgrading in 2019. Consequently, the aim of the multivariate analysis is to check if occupational upgrading is associated with ICT capital and the generosity of unemployment benefits.

The multivariate analysis consists of seven models that are displayed in Tables 1 and 2. Table 1 presents four of these models. The first is the empty model with no predictors. Model 1 introduces only control variables at the respondent level. Model 2 extends the first model by including measures for ICT capital and generosity of unemployment benefits. Finally, model 3 builds upon model 2 by adding the level two control variables. In the following, I display the formal specifications of the partial models:

$$\text{ISEI Score}_{ij} = \beta_0 + \varepsilon_{ij} + U_{oj} \quad \text{(Empty model)}$$

$$\begin{aligned}\text{ISEI Score}_{ij} = {} & \beta_0 + \beta_1\text{Sex}_{ij} + \beta_2\text{Age}_{ij} + \beta_3\text{Urbanisation}_{ij} + \beta_4\text{Citizenship}_{ij} + \beta_5\text{Education}_{ij} \\ & + \beta_6\text{Part Time Work}_{ij} + \varepsilon_{ij} + U_{oj} \quad \text{(Model 1)}\end{aligned}$$

$$\begin{aligned}\text{ISEI Score}_{ij} = {} & \beta_0 + \beta_1\text{Sex}_{ij} + \beta_2\text{Age}_{ij} + \beta_3\text{Urbanisation}_{ij} + \beta_4\text{Citizenship}_{ij} + \beta_5\text{Education}_{ij} \\ & + \beta_6\text{Part Time Work}_{ij} + \gamma_1\text{Unemployment Generosity}_j + \gamma_2\text{ICT Capital}_j \\ & + \varepsilon_{ij} + U_{oj} \quad \text{(Model 2)}\end{aligned}$$

$$\text{ISEI Score}_{ij} = \beta_0 + \beta_1\text{Sex}_{ij} + \beta_2\text{Age}_{ij} + \beta_3\text{Urbanisation}_{ij} + \beta_4\text{Citizenship}_{ij} + \beta_5\text{Education}_{ij}$$
$$+ \beta_6\text{Part Time Work}_{ij} + \gamma_1\text{Unemployment Generosity}_j + \gamma_2\text{ICT Capital}_j$$
$$+ \gamma_3\text{Real GDP Growth}_j + \gamma_4\text{GDP per capita}_j + \varepsilon_{ij} + U_{oj} \quad \text{(Model 3)}$$

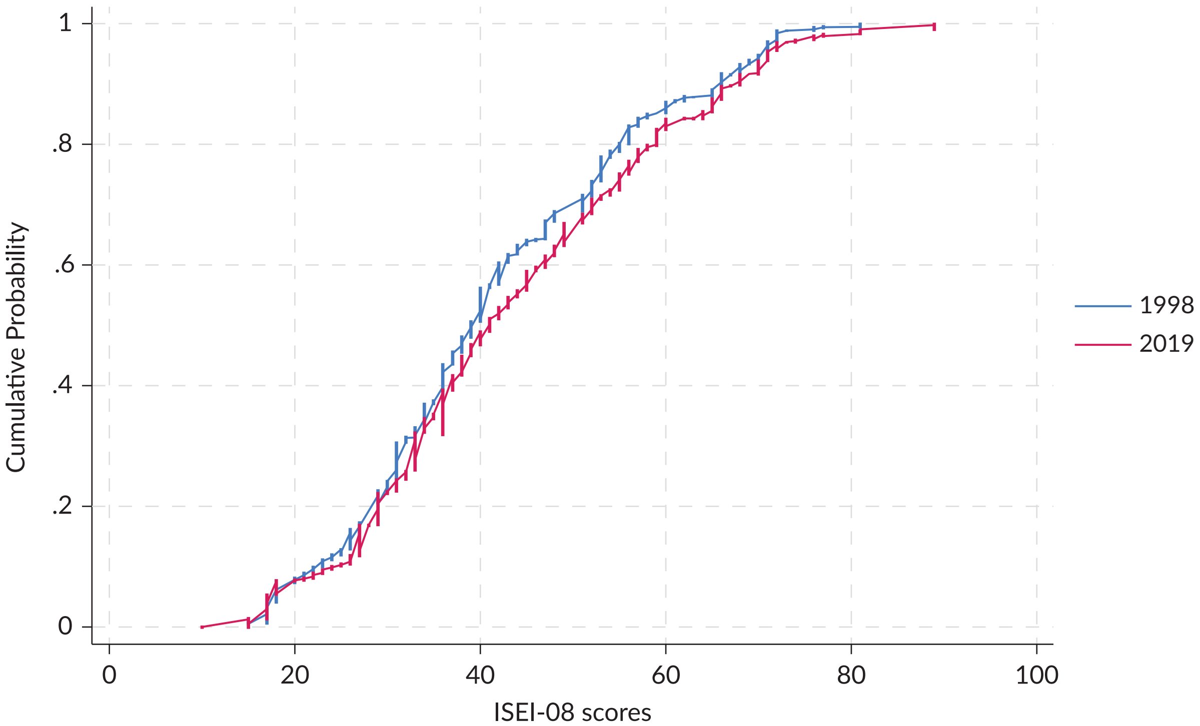


**Figure 3.** Cumulative distribution functions of ISEI-08 scores in the years 1998 and 2019 for the entire sample. Source: Author's own illustration based on EU-LFS data.

The empty model with no explanatory and control variables indicates an interclass correlation coefficient (ICC) of 0.2995. This leads to the conclusion that 29.95% of the variance in respondents' ISEI-08 scores can be explained by differences due to country-specific industries. The model is calculated to check if the assumption of dependence of observations is met. As indicated in the literature by Peugh (2010), it is assumed that multilevel models are appropriate if the ICC estimate is above zero and the design effect is higher than two. According to Peugh (2010, p. 91), the design effect captures the effect of independence violations on estimates of standard errors and further estimates the multiplier that is necessary to impose on standard errors to compensate for negative bias that arises from nested data structures. Both criteria are fulfilled in the empty model.

Model 1 indicates that the control variables perform as expected and that it is reasonable to include them in the full model. All variables are significant at the 1% level. More precisely, the model shows that (a) being female is associated with a lower ISEI-08 score than being male, (b) with each year of age, the ISEI-08 score increases, (c) compared to a rural location, ISEI-08 scores increase in more urban areas, (d) foreign passport holders are associated with a lower ISEI-08 score than local residents, and (e) part-time workers are associated with a lower SES than full-time workers. Further, the ICC in the model indicates that, even after including level one covariates, 22.35% of the variance in the respondents' ISEI-08 scores can be explained by differences due to country-specific industries.

**Table 1.** Multilevel random intercept regression models predicting ISEI-08 scores for the entire sample.

| | Empty Model | Model 1 | Model 2 | Model 3 |
|---|---|---|---|---|
| Sex (ref: Male) | | | | |
| 1: Female | | −1.902 ** (0.006) | −1.902 ** (0.006) | −1.902 ** (0.006) |
| Age | | 0.091 ** (0.000) | 0.092 ** (0.000) | 0.093 ** (0.000) |
| Urbanization (ref: Rural) | | | | |
| 1: Towns & suburbs | | 0.933 ** (0.007) | 0.939 ** (0.007) | 0.952 ** (0.007) |
| 2: Cities | | 1.885 ** (0.007) | 1.883 ** (0.007) | 1.868 ** (0.007) |
| Citizenship (ref: Native) | | | | |
| 1: Foreign | | −3.975 ** (0.012) | −3.965 ** (0.012) | −3.919 ** (0.012) |
| Education (ref: Lower secondary) | | | | |
| 1: Upper secondary | | 5.365 ** (0.007) | 5.376 ** (0.007) | 5.404 ** (0.007) |
| 2: Tertiary | | 19.139 ** (0.008) | 19.162 ** (0.008) | 19.209 ** (0.008) |
| Work status (ref: Full time) | | | | |
| 1: Part time | | −3.768 ** (0.007) | −3.762 ** (0.007) | −3.745 ** (0.007) |
| Unemployment benefits | | | 0.158 ** (0.004) | 0.111 ** (0.004) |
| ICT capital | | | −0.102 ** (0.002) | −0.002 (0.003) |
| GDP per capita | | | | 0.000 ** (0.000) |
| Real GDP growth | | | | 0.021 ** (0.001) |
| Intercept | 44.013 ** (0.596) | 32.092 ** (0.416) | 31.158 ** (0.446) | 32.150 ** (0.420) |
| $R^2$ level one | −/− | 0.3486 | 0.3279 | 0.3467 |
| $R^2$ level two | −/− | 0.5187 | 0.4447 | 0.5067 |
| ICC | 0.2995 | 0.2235 | 0.2474 | 0.2261 |
| $N$ | 19,917,152 | 19,917,152 | 19,917,152 | 19,917,152 |

Notes: ** and * denote statistical significance at the 0.01 and 0.05 levels; standard errors are reported in parentheses; pseudo-$R^2$ values are based on Snijders and Bosker (1994).

The second model shows for the whole sample that the more generous unemployment benefits are, the higher the ISEI-08 score of an individual is. An increase of unemployment generosity by one score point increases the ISEI-08 score by 0.158 points, ceteris paribus. Further, the results indicate that the higher the share of ICT capital on all assets within a country-specific industry, the lower is the SES of an individual. An increase of ICT capital in relation to all other assets by one percentage point decreases the ISEI-08 score by −0.102 ISEI-08 points, ceteris paribus. Both effects are significant at the alpha 1% level. The covariates perform similarly to the previous model. The Snijders and Bosker pseudo-$R^2$ values indicate that the model explains 32.79% of the variance on the individual level and 44.47% of the variance on the country-specific industry level.

In contrast to the previous model, model 3 indicates insignificant results for ICT capital if economic growth and GDP per capita are considered in the analyses. This could be because ICT capital is measured in relative terms. However, there may be a threshold effect, meaning that investments must meet a certain threshold in absolute numbers (independently of other production assets) to have an impact on SES. For instance, such effects are found in articles that consider the role of technology imports on employment (Bouattour et al., 2024). The effect of unemployment benefits on SES remains positive and significant at the 1% level. The level-one covariates show similar results as in the previous models. Further, the model indicates that an increase in GDP per capita by one unit decreases SES and shows that an increase in economic growth by one unit increases SES among the whole population. As the SBTC and RBTC hypotheses make different predictions about how various groups of workers are affected by the digital transition, the subgroup analysis is presented next.

Table 2 contains the main results of this article. This table shows the results of the full model for the subgroups and the corresponding interaction effects. Model 4 contains the results for individuals with low SES, model 5 the results for individuals with medium SES, and model 6 shows the results for individuals with high SES.

The analysis of the interaction effects for the different subgroups reveals that unemployment benefits have a moderating effect on the relationship between ICT capital and SES. Models 4, 5, and 6 indicate for each subgroup of workers a negative main effect of unemployment benefits on SES and a negative main effect of ICT capital on SES. However, the interaction effect between generosity of unemployment benefits and ICT capital is positive for each subgroup and significant at the 1% level. In other words, the results show that in a setting of generous unemployment benefits, an increase of ICT capital leads to a higher SES than in a setting of ungenerous unemployment benefits. However, the magnitude of the effect is relatively small in comparison to the level one covariates. For all models, Wald tests were conducted to check if the inclusion of an interaction term was necessary. The Wald test was significant for all three models, implying that it is useful to include the interaction term in the model. Further, the results show for each subgroup that the Snijders and Bosker pseudo-$R^2$ values are higher for level two than for level one. Moreover, the model explains the most variance for individuals with high SES. Figures 4, 5, and 6 display the interaction effects for each subgroup by predicting the SES of a respondent depending on the amount of ICT capital and the generosity of unemployment benefits in a country-specific industry.

The displayed interaction effects in Figure 4 show that depending on the generosity of unemployment benefits, a larger share of ICT capital can either reduce or increase ISEI-08 scores. More precisely, they indicate that in a setting of generous unemployment benefits, a larger share of ICT capital leads to an increase in ISEI-08 scores for the subgroup of low SES. The results also suggest that in a setting of less generous unemployment benefits, larger shares of ICT capital reduce ISEI-08 scores for workers with lower SES. This implies that depending on the generosity of unemployment benefits, both occupational upgrading and employment polarisation can be observed.

**Table 2.** Multilevel random intercept regression models predicting ISEI-08 scores for different subgroups.

| | Model 4: Low SES | Model 5: Medium SES | Model 6: High SES |
|---|---|---|---|
| Sex (ref: Male) | | | |
| 1: Female | −0.813 ** (0.004) | 1.452 ** (0.003) | −1.440 ** (0.006) |
| Age | −0.018 ** (0.000) | 0.010 ** (0.000) | 0.035 ** (0.000) |
| Urbanization (ref: Rural) | | | |
| 1: Towns & suburbs | 0.037 ** (0.004) | 0.011 ** (0.004) | 0.446 ** (0.008) |
| 2: Cities | 0.128 ** (0.004) | 0.053 ** (0.003) | 1.161 ** (0.007) |
| Citizenship (ref: Native) | | | |
| 1: Foreign | −1.395 ** (0.006) | −0.603 ** (0.007) | 0.875 ** (0.016) |
| Education (ref: Lower secondary) | | | |
| 1: Upper secondary | 1.142 ** (0.004) | 0.926 ** (0.004) | 0.370 ** (0.012) |
| 2: Tertiary | 1.661 ** (0.007) | 2.287 ** (0.005) | 5.659 ** (0.012) |
| Work status (ref: Full time) | | | |
| 1: Part time | −0.994 ** (0.004) | −0.201 ** (0.004) | −0.676 ** (0.009) |
| Unemployment benefits | −0.103 ** (0.003) | −0.067 ** (0.003) | −0.091 ** (0.006) |
| ICT capital | −0.042 ** (0.005) | −0.055 ** (0.004) | −0.105 ** (0.006) |
| Unemployment benefits x ICT capital | 0.006 ** (0.001) | 0.004 ** (0.000) | 0.012 ** (0.001) |
| GDP per capita | 0.000 ** (0.000) | 0.000 ** (0.000) | 0.000 ** (0.000) |
| Real GDP growth | −0.019 ** (0.001) | 0.007 ** (0.001) | −0.020 ** (0.001) |
| Intercept | 26.870 ** (0.212) | 38.152 ** (0.114) | 55.166 ** (0.157) |
| $R^2$ level one | 0.0701 | 0.1482 | 0.1500 |
| $R^2$ level two | 0.1073 | 0.3282 | 0.4356 |
| ICC | 0.3409 | 0.1945 | 0.0788 |
| $N$ | 6,822,227 | 6,262,962 | 6,831,963 |

Notes: ** and * denote statistical significance at the 0.01 and 0.05 levels; standard errors are reported in parentheses; pseudo-$R^2$ values are based on Snijders and Bosker (1994).

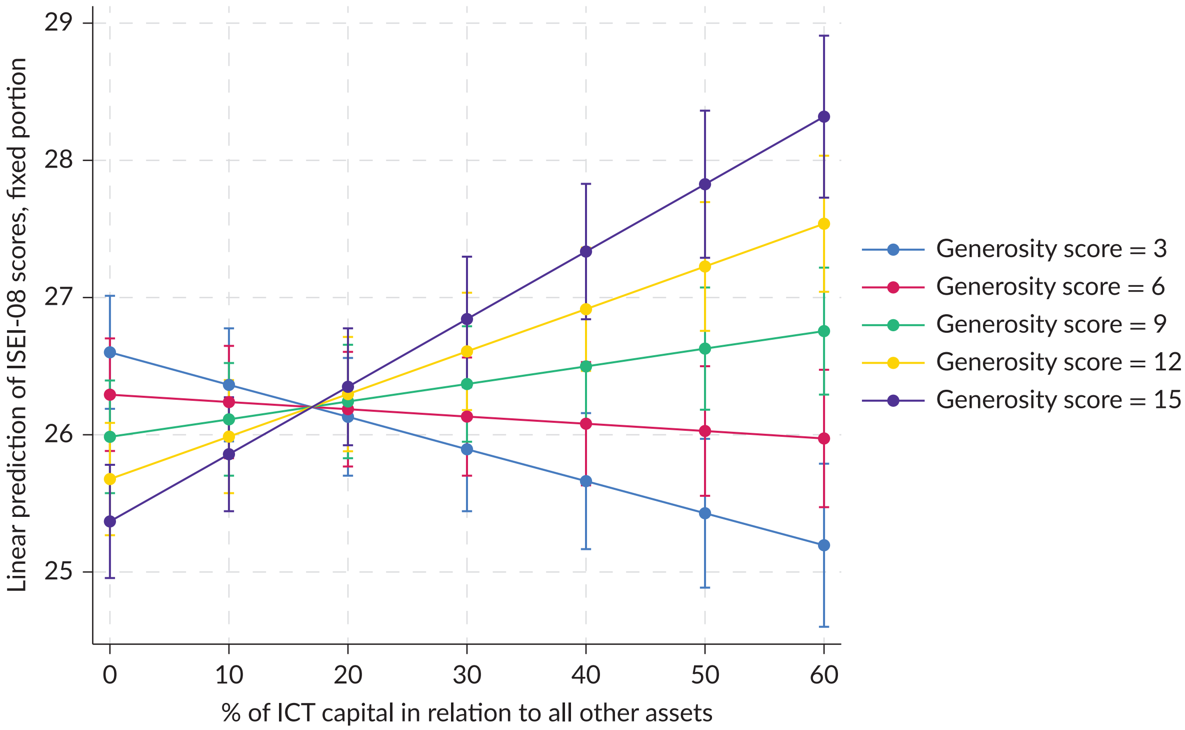


**Figure 4.** Predicted ISEI-08 scores with 95% confidence intervals for individuals with low SES. Notes: Prediction is based on generosity of unemployment benefits, amount of ICT capital, and the interaction term; higher generosity scores mean that unemployment benefits are more generous.

The interaction effects displayed in Figure 5 suggest that, in a setting of generous unemployment benefits, larger amounts of ICT capital tend to stabilise ISEI-08 scores instead of increasing them. However, the results imply that, in the absence of generous unemployment benefits, more ICT capital significantly reduces the ISEI-08 scores of individuals with medium SES. In other words, the interaction term suggests that ISEI-08 scores decline less at a given rate of ICT capital use when unemployment benefits are generous. Thus, generous unemployment benefits prevent a steeper decline in SES due to ICT-capital use. Regarding the entire employment structure, the results could mean that employment polarisation becomes more likely if unemployment benefits are less generous.

The interaction effect displayed in Figure 6 indicates, for individuals with a high SES, that more use of ICT capital increases ISEI-08 scores in a setting of generous unemployment benefits, while reducing it in a setting of less generous unemployment benefits. Hence, more generous unemployment benefits also improve the SES of individuals who already have a high SES. This result suggests that generous unemployment benefits could also further increase the ISEI-08 scores of individuals with a high SES, making occupational upgrading more likely. However, given the previous two graphs, the results also imply that ICT capital reduces SES in the absence of generous unemployment benefits, regardless of the considered groups.

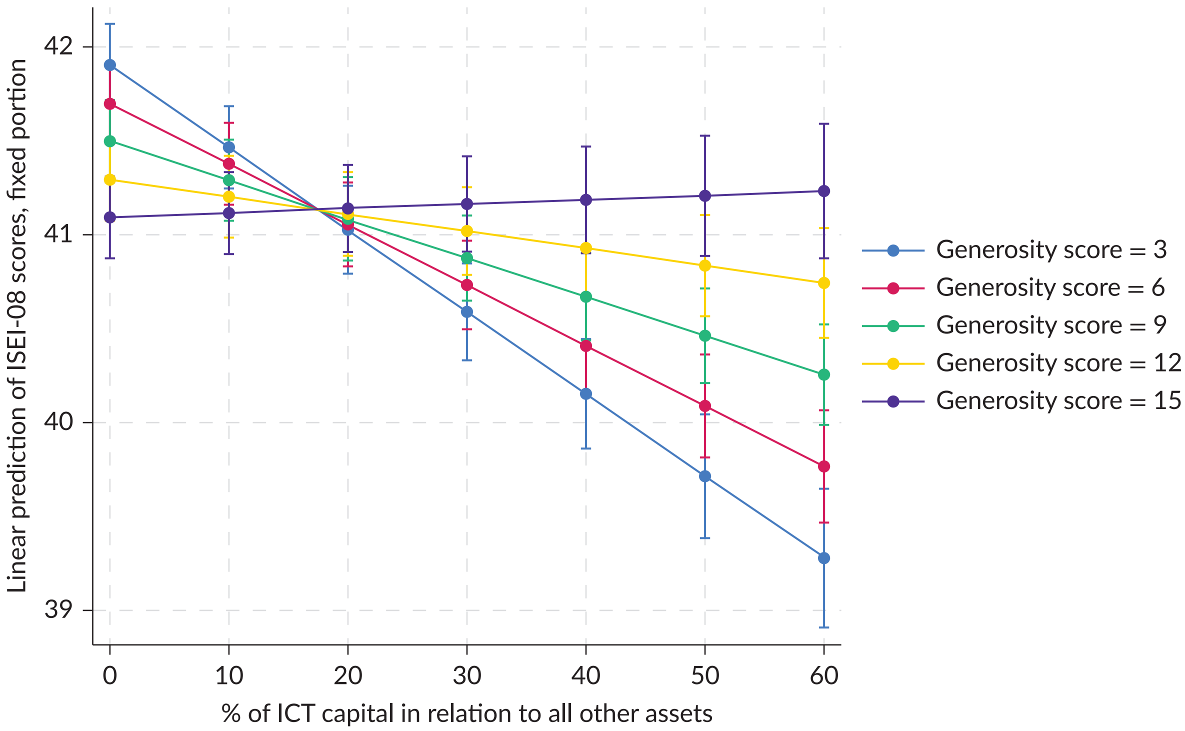


**Figure 5.** Predicted ISEI-08 scores with 95% confidence intervals for individuals with medium SES. Notes: Prediction is based on generosity of unemployment benefits, amount of ICT capital, and the interaction term; higher generosity scores mean that unemployment benefits are more generous.

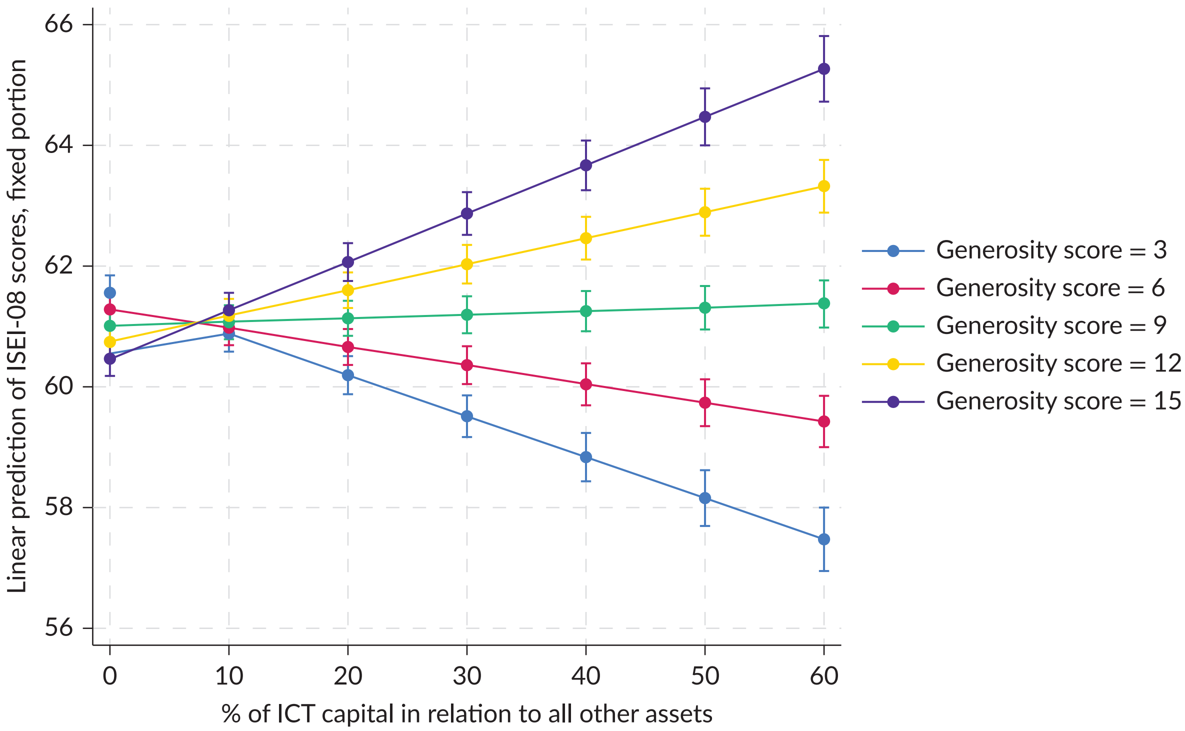


**Figure 6.** Predicted ISEI-08 scores with 95% confidence intervals for individuals with high SES. Notes: Prediction is based on generosity of unemployment benefits, amount of ICT capital, and the interaction term; higher generosity scores mean that unemployment benefits are more generous.

## 7. Discussion and Conclusion

By using multilevel models with random intercepts, this article investigated how ICT capital affects the SES of individuals depending on the generosity of unemployment benefits as part of social rights. The analysis is based on 12 European countries and 19 industries in the period from 1998 to 2019. In summary, the results indicate that generous unemployment benefits can hinder employment polarisation and lead rather to occupational upgrading, considering the results of the subgroup analysis. Related to the research questions, the results indicate that unemployment benefits as part of social rights could explain why heterogeneous results are observable empirically, if the institutional setting is insufficiently considered. Additionally, the results allow the interpretation that the generosity of social rights moderates the relationship between ICT capital and ISEI-08 scores in the selected countries and industries from 1998 to 2019. The results also suggest that in a setting of generous unemployment benefits, more use of ICT capital is rather associated with occupational upgrading, which confirms H1. This is due to the significance of the found interaction effects between the generosity of unemployment benefits and the use of ICT capital in the production of goods and services. However, H2 cannot be fully confirmed as the results indicate that within all SES groups, more ICT capital decreases ISEI-08 scores in the absence of generous unemployment benefits. If H2 were correct, the result would indicate a positive regression coefficient of ICT capital independently of the generosity of unemployment benefits for the high-SES group.

The results are consistent with the literature on the effects of institutions in the relationship between technology and employment. In line with Haapanala et al. (2023), Kristal and Cohen (2017), Oesch (2015), and Fernández-Macías (2012), who argue that unions, welfare state regimes, or institutions in general influence the technology–employment nexus, this article finds that the generosity of unemployment benefits mitigates how technology affects employment patterns. Accordingly, the EPSR can be a tool to foster social inclusion by shaping the job structure in such a way that the labour market allocates better jobs to work-dependent individuals.

The results are also in line with other authors who consider the effects of welfare benefits on employment. As argued by Gangl (2006), who finds that unemployment benefits prevent downward occupational mobility, this article finds that generous unemployment benefits can hinder reductions in SES due to technological change. Further, Biegert (2017) confirms that unemployment benefits can be seen as a job search subsidy leading to better job matches, which this article also argued in relation to the digital transition.

There are also some limitations to the results of this article. First, the values for the dependent variable, ISEI-08 scores, are based on three-digit ISCO-08 and ISCO-88 codes, since in the EU-LFS data, four-digit codes are not provided. Using four-digit ISCO codes has the advantage of increasing the accuracy of ISEI-08 scores, as those codes show a greater variety in values than three-digit ISCO codes. Second, a limitation of using EU-LFS is that it is a repeated cross-sectional dataset. This dataset is not suitable for longitudinal analysis, as individuals are not tracked over time. Hence, the use of panel data would increase the validity of the findings in terms of causality. Third, Eastern European countries are not part of this analysis, as CWEP data for those countries is not available in the considered timespan. This may reduce the external validity of the findings beyond the countries and industries considered. Given the distinct historical and socio-political past of Eastern European countries in comparison to other EU countries, this could affect the generalisability of the results.

Future research should also take other welfare state benefits into account. Although unemployment benefits are an important part of social rights, they do not cover all aspects. If recipients drop out of unemployment insurance by reaching the maximum period of entitlement, or if people are not eligible for unemployment benefits (for example, if a person does not fulfil the minimum period of employment for receiving the benefit), then the generosity of minimum income schemes is central to individual employment decisions, especially for individuals with low to medium SES. This may also explain why the found moderating effect is the highest for the high-SES group.

Moreover, from a political economy perspective, it should be noted that the effect of the digital transition on national labour markets could depend on a country's integration into global value chains (GVCs). For instance, the literature indicates that the value along GVCs is not added equally, and instead so-called smile curves are observable. Smile curves indicate that higher value is added at the margins than in the middle of GVCs (Meng et al., 2020). This could also affect job creation, as the demand for labour may differ depending on a country's position in a product's GVC.

The obtained results lead to several conclusions regarding the goals of the EPSR and its implementation. First, the results imply that the impact of the digital transition on employment can be influenced by granting social rights, such as unemployment benefits, to work-dependent individuals. According to the theoretical considerations, the results imply that unemployment benefits influence the labour market behaviour of firms and employees. Hence, the EPSR could be the charter that enables policymakers to intervene in the relationship between technology and employment. Second, if the goal of the EPSR is to provide good employment, then also additional political measures are necessary to ensure that the worse-off are not left behind. For instance, while opting for a scenario of occupational upgrading can increase the SES among the employed, further educational or vocational policies could be needed to upskill individuals who cannot keep pace with the requirements of more skill-demanding jobs. Otherwise, the employment rates of those groups might be reduced. In this regard, there is evidence in the literature that generous unemployment benefits might also lead to more investment in workers' skills by themselves, as they are more likely to take risks in investing in their human capital (Sjöberg, 2008). However, upskilling measures are also limited in their capacities and especially the long-term unemployed could require additional targeted support. Third, from a European perspective, Figure 1 shows that the generosity of unemployment benefits differs among European countries. Accordingly, the digital transition might reinforce existing inequalities between European countries in regard to employment outcomes. If differences in benefit generosity lead to diverging employment trajectories (namely occupational upgrading and employment polarisation), then this could also affect further socio-economic inequalities like wages or employment security that result from different occupational structures. But let us end on a note of optimism. While the digital transition affects employment, there are ways to govern this transition, which could mitigate the negative impact of new technologies on employment.

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## Conflict of Interests

The author declares no conflict of interests.

## Data Availability

This study uses data from Eurostat's EU Labour Force Survey, 1998 to 2019, 18 January 2024 (https://doi.org/10.2907/LFS1983-2022); data access can be requested from Eurostat. EU-KLEMS data are publicly available at the Luiss Lab of European Economics website (https://euklems-intanprod-llee.luiss.it). CWEP data are available after a short registration at https://www.cwep.us. OECD data are also publicly available at the OECD Data Explorer (https://data-explorer.oecd.org). The responsibility for all conclusions drawn from the data lies entirely with the author.

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