Automatisation and basic income: distributional implications for selected European countries

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Abstract

Our research examines how the income distribution and overall welfare might develop in different European countries amid potential shifts in the job structure. These shifts are conceptualised through various scenarios, shaped by assumptions about employment trends arising from automation effects. We use EUROMOD, a tax and benefit microsimulation model for the European Union, and data from the European Union Statistics on Income and Living Conditions survey (EU-SILC) to calculate the changes in disposable income and inequality indicators under different automatisation and policy scenarios following Eurofound projections. With a discrete choice model we further estimate female labour supply and simulate welfare effects of providing a version of Universal Basic Income to all single unemployed and inactive women. Results indicate that the countries with more generous welfare systems not only experience smaller increase in income inequality as a consequence of the automatisation but also have a higher share of winners of the policy reform even in the scenario with the faster uptake of the automatisation.

1. Introduction

Over the past decade there has been a growing concern about an increase in inequality and poverty, and existing tax and benefit systems throughout Europe are being re-examined in light of their capacities to offer adequate protection. Rising inequality is the consequence of many structural factors: globalisation, automatisation and digitalisation, changes in tax, social transfers and labour market policies, climate changes, migration (Piketty, 2014; Atkinson, 2015; Milanović, 2016). The individual and combined effects of these megatrends on the world of work and their socio-economic consequences are still to be fully understood and addressed. However, despite differences in the methodology and results, there is almost a consensus at the global level that due to automatisation some occupations might experience consequences like: job losses, more temporary jobs, increased inequality and polarisation of incomes; more geographical and sectoral re-allocation of resources; polarisation of skills (Colombino & Islam, 2022).

This report studies how the income distribution and overall welfare, measured as the share of winners in the utility function, may evolve in different European countries under a range of potential scenarios for the future changes in the job structure. Scenarios are based on the assumptions of the employment trends resulting from the automatisation effects. Comparison of the current economy and hypothetical economy with different degrees of automatisation will then serve as a baseline for testing the implementation of new redistributive policy. We consider a version of the Universal Basic Income (UBI), a policy that has been widely debated in recent years across number of countries as a potential response to the challenges of income inequality, the uptick in non-traditional work arrangements facilitated by technological advancements or the looming possibility of unemployment resulting from automation. Various studies have found that UBI has the potential to reduce poverty and inequality, but its fiscal and distributional effects depend on the design and financing options (Browne & Immervoll, 2017; Colombino, 2019, OECD, 2017a; b). Van Parijs and Vanderborght (2017) present a comprehensive case for UBI, arguing it offers a more efficient and fair alternative to conditional welfare programs, emphasising its potential to reduce bureaucracy, grant genuine financial freedom, and address social inequalities effectively compared to targeted benefits. Browne and Immervoll, (2017) assess UBI's fiscal and distributional consequences across diverse countries through microsimulation methods. Findings highlight both the merits and drawbacks of existing social safety nets. Other authors add labour supply models to microsimulation framework to asses the feasibility and possible impacts of UBI compared to existing social welfare programs and tax schedules (Colombino, 2015; Islam & Colombino, 2018; Colombino & Islam, 2022). We built on that framework and choose a Universal Basic Income that replaces current unemployment benefits in several European countries to determine social welfare effects of this policy reform in case of different scenarios for the future of work affected by the automatisation. Our approach differs from similar studies as we pay particular attention to projections of job losses and job gains due to automatisation, with a focus on sectors and occupations instead of the total economy which other papers in the field use when assessing effects of the UBI. In that manner, we take into account structural features of the labour markets and show how those impact distributional effects of the automatisation followed by UBI reform.

This report is structured in the following way. Section 2 reviews literature dealing with the employment effects of the automatisation. The methodology is developed in Section 3. Section 4 presents the results and Section 5 concludes the report.

2. Employment effects of automatisation

The impact of automation[1] and technological change on the world of work was seen as a generally positive trend until the emergence of the fourth industrial revolution (Brynjolfsson & McAfee, 2014; Pouliakas, 2018). With artificial intelligence and robotics it is believed that there is a higher potential that some of the existing jobs will disappear (Hogarth, 2018). Estimates show that the potential impact of job automation on the country's employment is driven by employment shares across sectors and the relative proportion of jobs at high risk of automation in each of those sectors (PwC, 2017).

The seminal paper in the field by Frey and Osborne (2013) estimates the probability of automatisation for 702 detailed occupations and finds that about 47% of total US employment is at high risk of automatisation over the next decade or two. Authors predict that most workers in transportation and logistics occupations, together with a large part of office and administrative support workers, and labour in production occupations, are at risk of losing a job. Following the occupation-based approach of Frey and Osborne (2013), Arntz *et al.* (2016) develop a task-based approach, looking at the heterogeneity of workers' tasks within occupations, to estimate the risk of automatisation for jobs in 21 OECD countries. Their estimates are lower compared to the occupation-based approach: on average, 9% of jobs are automatable but with shares of automatable jobs spanning from 6% in Estonia to 12% in Austria and Germany.

[1] Automation is defined as the replacement of people working in some jobs by robots, artificial intelligence or machine learning technologies.

Extending the coverage to 32 OECD economies Nedelkoska and Quintini (2018) show that close to one in two jobs are likely to be significantly affected by automation. Suta *et al.* (2018) found that 46% of the 2-digit occupations in the EU are susceptible to being automated. The highest shares of employees in the EU27 with high automation risk are found among subsistence farm workers, machine and plant operators, assemblers, handicraft and printing workers, construction workers and other manufacturing workers (all higher than 15%) while the lowest shares (less than 5%) are among street services workers, managers and care workers (Eurofound, 2021).

Eurofound (2019) uses global macro-sectoral econometric model to make assessment of the potential employment impact of automation. Their projections include the trajectory of employment in different occupations (ISCO 2-digit level) from 2018 to 2030. Following the literature in the field Eurofound determines the potential for automation based on technical grounds. How much of this potential will be fulfilled by 2030 depends on the cost of automation and the scale of assumed investments.

Regarding the costs of automation, Eurofound looks at the cost of automating a job from within the range of industry estimates in 2018 and assume that the costs fall over time as technology develops. Multiplying these costs by the number of jobs assumed to be displaced gives a required investment figure. Based on the estimated number of jobs at the risk of automation and investment levels needed to automate routine jobs and costs of training workers in these jobs, model predicts two scenarios: a high-cost case, with slower uptake of automatisation and fewer job losses, and a low-cost case in which uptake is faster and job losses are larger. These estimates suggest that the total job loss due to automatisation by 2030 will be about 10% in the high-cost scenario and 16% in the low-cost scenario. They are calculated against a baseline scenario in 2030 which assumes no automatisation and is based on Eurostat population and short-term macroeconomic forecasts from Cedefop (2018).

Compared to similar research in the field our paper puts a special emphasis on projecting jobs losses and gains due to automatisation. Instead of assuming a linear decrease of employment due to automatisation across the whole economy, we look at detailed expected employment changes among different occupations. In that regard, novelty of our approach lies in assessing the effect of the policy reforms by allowing the interaction of several factors like the occupational structure of the economy and its tax and benefit system. Further to that we develop a methodology that allows the calculation of the impact of expected employment changes on disposable incomes which can be applied to different employment categories, not only occupations (such as sectors, job security status, age and gender structure, etc).
novelty and how we fill the gap in the literature.

3. Methodology

Our methodology for estimating the effects of automatisation and policy reforms on income distribution and overall welfare consists of several steps. We first investigate suggested employment changes in different European countries due to automatisation, based on the projections by Eurofound (2019) and apply them to the EU-SILC 2018 data.

We decided to base our analysis on Eurofound (2019) as it includes the most comprehensive projections of share of jobs at potential risk of automatisation across sectors and occupations of the economy and covers all European union member states. Besides academic papers mentioned in the previous section grey literature in a similar manner covers from one to several countries and/or provide projections for the economy as a whole, like: McKinsey Global Institute (2017) for France, Germany, Italy, Spain and the United Kingdom (UK), PwC (2020) for UK, PwC (2017) for selected EU countries but providing projections only for the whole economy. These studies have mainly taken the standard approach, of first determining tasks most susceptible to automatisation and then assess importance of these tasks for jobs in different sectors.

The methodology Eurofound uses for the assessment of changes in employment is based not only the risks each occupation is facing, but also on investments required to replace workers with machines/software and changes to each sector's supply chain (Eurofound 2019, p. 6). Risks of automatisation are higher for jobs for which tasks normally carried out include numerous routine tasks, which can be easily automated. The model also accounts for investment levels needed to automate routine jobs and costs to train workers to work in these jobs. Additionally, the model includes estimates of the impact of global supply chains on employment, most notably shift towards purchases of IT equipment and software.

Eurofound results show that, depending on the automatisation scenario, by 2030 from 12.6% to 17.2% of the jobs in the EU28 will be replaced by robots or another form of automation. This range is broadly consistent with the figure of 14% in the results reported by Nedelkoska and Quintini (2018) and the range 14-18% in the results from Suta *et al.* (2018), cited earlier. On the other hand, these estimates are considerably lower than the range of automation rates suggested in many other studies, for example by McKinsey Global Institute (2017) for Germany (27–47%).

The EU-SILC is a European-wide harmonised survey, conducted under the Eurostat guidelines, with the goal to gather timely, comparable data on living conditions, social exclusion, poverty and income inequality, health and well-being.[2] Detailed data on income and taxes are collected, as well as information on material deprivation, labour, housing, childcare, health, access to and use of services, and education. Although primarily a social policy instrument that addresses the information needs of policymakers and is used for social monitoring at the European level, EU-SILC is also closely geared to the needs of researchers and provides an excellent database for evidence-based research on a wide variety of aspects of income, income poverty, material poverty, health, and well-being in Europe. EU-SILC provides cross-sectional and longitudinal data which are composed of a fixed core module and annually changing ad-hoc modules. Launched in 2003 and EU-SILC is currently implemented in all EU Member States and in 11 non-EU countries.

In the second step, we link them with EUROMOD,[3] tax and benefit microsimulation model for the European Union, input data to analyse changes in disposable income due to automatisation under current tax and benefit policy regimes. As integrated EU-wide model EUROMOD is used to simulate individual tax liabilities and social benefit entitlements according to the rules in place in each of the member states. Similar to other microsimulation models it is a tax and benefit calculator based on micro-data on income, earnings, labour force participation as well as on various socio-demographic features. EUROMOD is designed for making cross-country comparisons and for answering 'what if' questions such as what would happen when we substitute ('swap') tax or a benefit system from one country to another (Sutherland & Figari, 2013). It that enables researchers and policy analysts to calculate the effects of taxes and benefits on household incomes and work incentives for the population of each country and for the EU as a whole. Recently, an extension to the model allowed the evaluation of the budgetary effects and the equity impact of reforms to indirect tax policies (De Agostini *et al.*, 2017)

In the third phase, we focus on assessing the effects of implementing Universal Basic Income. Specifically, we conduct simulations to understand the impact on income inequality when UBI replaces unemployment benefits. Finally, we are interested in the welfare consequences of such a reform and for that purpose estimate a model of labour supply of single female households.

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2 https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions

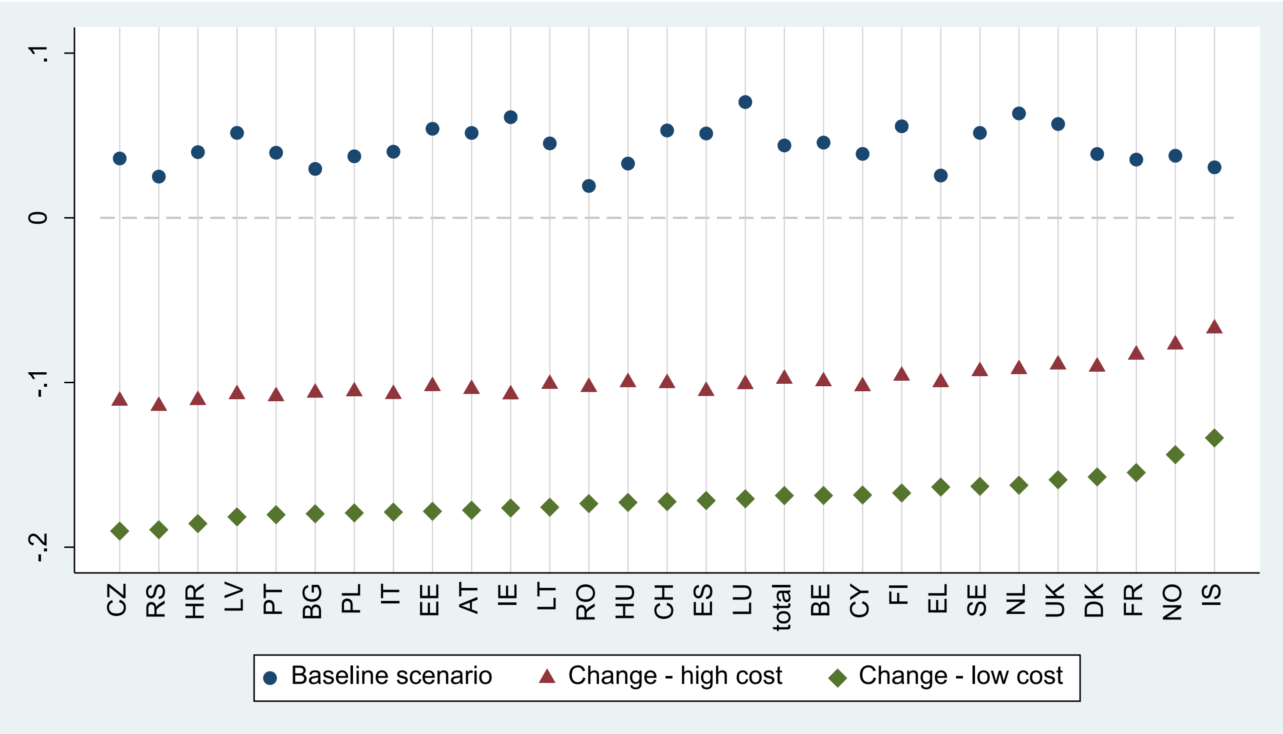
3 https://euromod-web.jrc.ec.europa.eu/

3.1. Employment effects of automatisation scenarios

Figure 1 presents changes in employment for each country depending on the occupational structure of employment. When a country has a higher percentage of occupations that are at a higher risk of being automated, the overall effect on employment will be higher and vice versa. The blue dots in Figure 1 represent the employment change if there were no effects of automatisation based on the population and short-term macroeconomic forecasts. Employment in this scenario would be higher by 4.4 percentage points on average. The lowest increase in employment is predicted for Romania, Serbia and Greece (2.6% or lower) and the highest increase for Luxemburg, Netherlands and Ireland (6% or higher).

The red triangles and green squares in Figure 1 present the net effect of the high-cost and low-cost automatisation on employment. This is calculated as the difference between the positive changes, predicted in the baseline scenario, and the negative changes predicted as a consequence of the automatisation. The average effect of the automatisation is estimated at 9.8 percentage points for the high-cost scenario and 16.8 percentage points for the low-cost scenario. The countries with the highest effects of low-cost automatisation are mainly Eastern-European economies: Czech Republic, Serbia, Croatia, Latvia, Bulgaria and Poland, in which the negative effect is 18 percentage points or higher, while the lowest effect - 16 percentage points or lower - are recorded in Scandinavian countries: Norway, Iceland and Denmark, as well as in France and Netherlands.

Figure 1. Changes in employment rates as a consequence of the automatisation

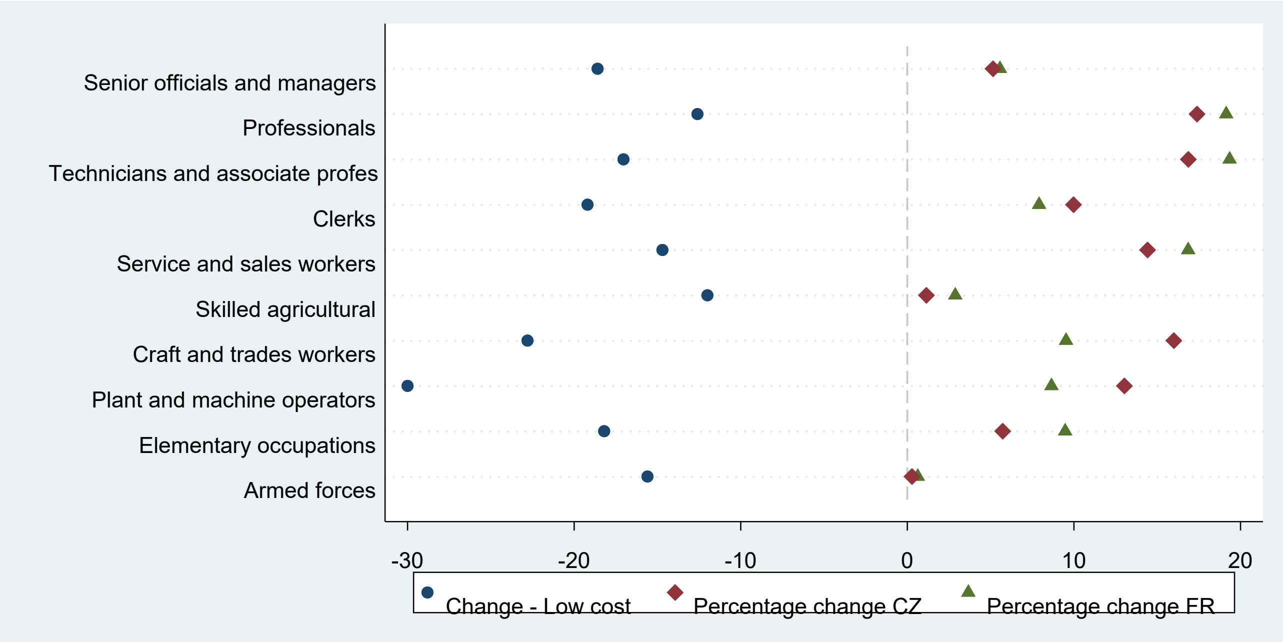


Notes The graph does not include Germany, Slovenia and Malta, as for these countries ISCO codes are available only on the 1st level of ISCO categorisation and Slovakia, as the occupations are not defined.

Source: Own calculation based on 2018 EU-SILC data and Eurofound (2019)

To illustrate differences in occupational structures, we compare France and the Czech Republic in Figure 2. In Czech Republic there is a higher share of workers who are plant machine operators (ISCO group 8) and craft and trade workers (ISCO group 9) than in France. Since these occupations are expected to have an above-average decrease in employment as a consequence of automatisation, this leads to a higher expected overall effect of automatisation in the Czech Republic than in France. Furthermore, France has a higher share of workers in occupations such as Professionals (ISCO 2), Technicians and associate professionals (ISCO 3) and Service and sales workers (ISCO 5), which are expected to have lower employment losses. This further contributes to the differences in the overall projected employment losses between the two countries. Although the difference between France and the Czech Republic is one of the most prominent ones, similar arguments apply to other countries which have high and low effects of automatisation.

Figure 2. Occupation structure in two selected countries and employment changes by occupation



Notes: Blue dots represent the percent changes in employment in the cases of low costs of automatisation, by occupations (ISCO Level 1), based on the Eurofound (2019) estimates of changes in employment in different occupations (ISCO Level 2). Red diamonds and green triangles represent the shares of each occupation in Czech Republic (CZ) and France (FR). The figure illustrates differences in occupational structure between the countries and how these differences result in different estimates in overall employment effects as documented in Figure 1.

Source: Own calculation based on 2018 EU-SILC data and Eurofound (2019)

3.2. Imputing employment projections into EU-SILC microdata

The next step in our analysis is to translate Eurofound employment predictions by occupations into 'job losses' and 'job gains' in the EU-SILC microdata. To that end, we first calculate the weighted number of job losses for each occupation in each country and find the persons within each country/occupation most likely to lose their jobs based on their employment vulnerability and the likelihood of employment. Employment vulnerability is derived from employment and contract status (self-employed, contributing family members and temporary wage workers are vulnerable), working time (part-time workers are considered vulnerable) and working experience (those with under two years of experience are considered to be vulnerable). Each vulnerable status is represented by a dummy variable, and the sum of these variables makes the employment vulnerability index which ranges from 0 (no vulnerabilities) to 3 (all vulnerabilities). On average about 26.3% of workers are in vulnerable categories, with part time and temporary jobs being among the most frequent vulnerabilities (17% and 12,1% respectively).

When individuals within the same country/occupation cluster have the same number of vulnerabilities, we use the likelihood of employment as an additional criterion to select those who are going to lose jobs. The likelihood of employment is calculated by estimating country-gender probit models of employment, conditional on determinants such as marital status, age and its square, education level and number of children (three variables: children aged 0 to 2; 3 to 6; and 7 to 14). For those selected for job losses, their entire gross labour income (variables py010g and py050g)[4] is deducted.

Similarly, for occupations and scenarios which are projected to have increase in employment, we first calculate the weighted number of job gains for each occupation in each country and find the persons within each country most likely to occupy these jobs. The selection process here is based on likelihood of employment (already described in the previous paragraph), and occupation similarity (if the person belongs to the same ISCO 1-digit group). If such persons are not found within similar occupations the selection is based solely on the likelihood of employment within each country. It should be noted that the 'job losses' were imputed first, and that pool is also included in the pool of potential 'job gainers', thus allowing for the transition between jobs because of automatisation.

In the next phase, we impute wages that persons would earn on gained jobs as the average wages in the clusters formed by country, occupation, person's educational level, gender and age group (occupation wages). If a person has no prior occupation or is not drawn into the cluster of job finders based on their occupation, their future wages are determined based on their country, educational level, gender and age group (country wages). For those selected for job gains, we impute their income variable into the gross labour income variable (variable py010g).

3.3. Selection of countries and link between EU-SILC and EUROMOD input data

To study how income distribution and overall welfare will change as a result of automatisation and proposed policy changes, we use EUROMOD, a tax-benefit microsimulation model for the European Union. While EUROMOD is based on the EU-SILC data, actual input data, also available for use, slightly differ from EU-SILC as each EUROMOD country team adapts the data according to their tax and benefit

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4 We opted to change gross labour income variables instead of net for two reasons. Firstly, net income variables are not defined in some countries (CY, CZ, DK, FI, IS, NL, NO, UK). Secondly if we want to monitor the overall changes in the tax and benefit systems, we need not only to replace net wages, but also the changes in taxes that will be collected based on these wages.

rules. Most importantly for our study, EUROMOD input data do not contain ISCO 2-digit occupation (in many cases, there is no information on the occupation at all). Thus the first part of our simulation had to be performed on the EU-SILC.

We merge simulation results from EU-SILC data with EUROMOD input data to create alternative datasets for the calculation of the effects of automatisation and the policy reforms. For some countries, such as Austria, Italy, Iceland, Norway, Serbia, Switzerland and the UK, EU-SILC and EUROMOD input data cannot be matched or EUROMOD input data do not exist. Given that we already excluded some EU countries due to the unavailability of 2-digit occupation information (Germany, Slovenia, Malta and Slovakia), and that for some countries we cannot match EU-SILC and EUROMOD data, calculation of the effect of automatisation and policy changes for the whole EU is not possible.

The selection process led us to focus on the following countries: the Czech Republic, France, Spain and Romania. Our choice of the first two is based on the fact that they have the highest and the lowest effects of automatisation and, as presented in Figure 2, distinct differences in occupational structure. We chose Spain as a representative of Southern European region, which also have a high anticipated increase in employment by 2030 in the baseline scenario (no automatisation) and Romania as a representative of South-East European countries, which also has among the lowest increase in employment in the baseline scenario. Both Spain and Romania have a moderate effect of automatisation according to our simulations.

After merging changes in the labour market status and labour income variables in the EU-SILC with EUROMOD input data, we change all variables that are relevant for microsimulation and calculation of the disposable income (Appendix 1).

3.4. Changes in the disposable income resulting from policy reform

3.4.1. First round static effect

There are three different input databases for EUROMOD for each automatisation scenario: baseline, high-cost and low-cost (Table 1). Table 1 summarises the changes made to the databases (row description). We calculate two effects of automatisation: a) for the high cost scenario as a difference in inequality indicators based on variables DISP_Y_H and DISP_Y_B; and b) for the high cost scenario as a difference in inequality indicators based on variables DISP_Y_L and DISP_Y_B.

After implementing a policy reform we will have another set of disposable incomes for each scenario, presented in the last row in the Table 1

Table 1. Main outcome variables, depending on automatisation scenario

	Original data	'Baseline' scenario effect	High costs scenario	Low costs scenario
Description	Original data set obtained from EUROMOD	Original data updated for the changes that would occur by 2030 only due to demo-graphic and macro effects	Baseline scenario data updated for the changes that would occur in the case of high costs of automa-tisation and lead to lower level of automa-tisation	Baseline scenario data updated for the changes that would occur in the case of low costs of automati-sation and lead to higher level of autom-atisation
Main output Variable 1	DISP_Y	DISP_Y_B	DISP_Y_H	DISP_Y_L
Main output Variable reform	DISP_Y_R	DISP_Y_B_R	DISP_Y_H_R	DISP_Y_L_R

The calculation of the reform effects will be based on inequality indicators based on disposable income arising from current tax and benefit system and policy reforms. We will have several variants of policy effects:

- *effect of the policy reform without automatisation effects:* effect of the reform in the baseline scenario calculated as the difference between the indicators based on DISP_Y_B and DISP_Y_B_R;
- *effect of the policy reform- high automatisation costs*: effect of the reform in the case of high-cost automatisation calculated as the difference between the indicators based on DISP_Y_H and DISP_Y_H_R;
- *effect of the policy reform - low automatisation costs* - the effect of the reform in the case of low-cost automatisation calculated as the difference between the indicators based on DISP_Y_L and DISP_Y_L_R.

3.4.2. Labour supply and welfare

Recent discussions on Universal Basic Income in developed countries underscore its fundamental principle of providing consistent, unconditional payments to individuals, although interpretations and justifications vary widely. This socio-economic policy ensures that every adult citizen receives fixed, unconditional cash payments regardless of their employment or income status. Also known as guaranteed income, UBI aims to alleviate poverty and secure financial stability irrespective of economic conditions (Van Parijs & Vanderborght, 2001; Santens, 2016; Browne & Immervoll, 2017).

However, its superiority over traditional social benefits hinges on economic context, implementation specifics, and societal values. UBI holds potential to simplify welfare systems, reduce poverty, and stabilise economies amidst technological change, yet challenges include cost, potential work disincentives, and efficient resource allocation. Policymakers must carefully weigh these factors within their economic and social frameworks to determine the most effective approach. These varied definitions underscore the diverse goals and potential benefits of UBI, ranging from poverty reduction and economic stimulus to advancing social justice and preparing for a future with fewer traditional jobs. As automatisation and evolving work dynamics reshape the economic landscape, UBI is positioned by its proponents as a pro-active response to mitigate potential job losses due to technological advancements.

The effectiveness of UBI compared to traditional social benefits depends on multiple factors, including economic context and implementation details. While UBI shows promise in simplifying welfare systems, alleviating poverty, and providing economic stability in the face of technological change, it must contend with challenges such as potential impacts on work incentives. Colombino (2015) discusses the feasibility and potential impacts of UBI compared to traditional social welfare programs in Italy, using simulations to explore various scenarios. He focuses on the labour market effects, economic efficiency, and the interplay with tax policies highlighting the transformative potential of UBI but also caution that its success depends on careful design and implementation. Islam and Colombino (2018) model labour supply for singles and couples, simulating household decisions under specific tax-transfer rules constrained by budget limits for a sample of eight European countries: Austria, Belgium, France, Germany, Ireland, Italy, Luxembourg and the United Kingdom. Results consistently favour the General Negative Income Tax over other rules, including existing policies. Unconditional Basic Income is preferred over Conditional Basic Income, which may reduce labour supply and create poverty traps. In-Work Benefits perform poorly compared to both General Negative Income Tax and Unconditional Basic Income. Using behavioural microsimulation and numerical optimisation, Colombino and Islam (2024) seek an optimal tax-transfer rule based on household disposable income modelled as a 4th-degree polynomial in taxable income plus a constant. Their model integrates equilibrium constraints and assesses labour demand changes. They analyse three scenarios: Status quo, Jobless (20% reduction in medium-skill jobs), and Polarised (20% reduction in medium-skill jobs, with 10% increase in high-skill and low-skill jobs). Comparing current tax-transfer rules with polynomial optimal rules across France, Germany, Italy, and Luxembourg using 2015 EU-SILC data, they find the polynomial optimal rules consistently outperform current ones in social welfare across all scenarios. Except for Luxembourg, these optimal rules resemble a combination of flat tax and Universal Basic Income.

This study investigates the feasibility and implications of implementing Universal Basic Income in three European countries using microsimulation techniques. It aims to analyse how UBI could potentially affect labour markets and welfare outcomes within each nation's unique demographic, economic, and tax policy contexts. We exclude France from our welfare analysis because the monotonicity and concavity conditions are not satisfied. Additionally, the restricted optimisation conditions do not allow the likelihood function to converge. Therefore, France is omitted from this part of the study.

Key aspects of our investigation include examining diverse responses in labour supply and welfare outcomes of replacing current unemployment benefits with the universal amount of the unemployment benefit to all single unemployed and inactive women across these countries. This analysis indicates significant implications for the design of welfare policies in different cost scenarios (baseline, high cost, and low cost).

4. Results

4.1. Changes in income inequality and poverty due to automatisation

Figure 3 represents changes in the disposable income due to automatisation for high-cost (blue long-dash line) and low-cost (red full line) scenarios. The vertical axis depicts percent changes in disposable income compared to baseline (pre-automatisation) income distribution, short-dash and dotted lines average change for the high- and low-cost scenario respectively, while the long dash and full line represents change at different parts of the income distribution for the high- and low-cost scenario respectively.

Results reveal that automatisation will lead to decrease in average disposable income in all the countries with the lowest decrease observed in France - by about 1.7% for the high-cost scenario and 2.8% for low-cost scenario. This is in line with projected changes in employment due to automatisation which were also the lowest for France out of these four countries (see Figure 1). For Spain and Czech Republic the projected decrease in employment was higher than in France and this resulted in more prominent reductions in average disposable income - by 3.3% and 3.6% in the high-cost scenario and by 5.0% and 5.7% in the low-cost scenario.

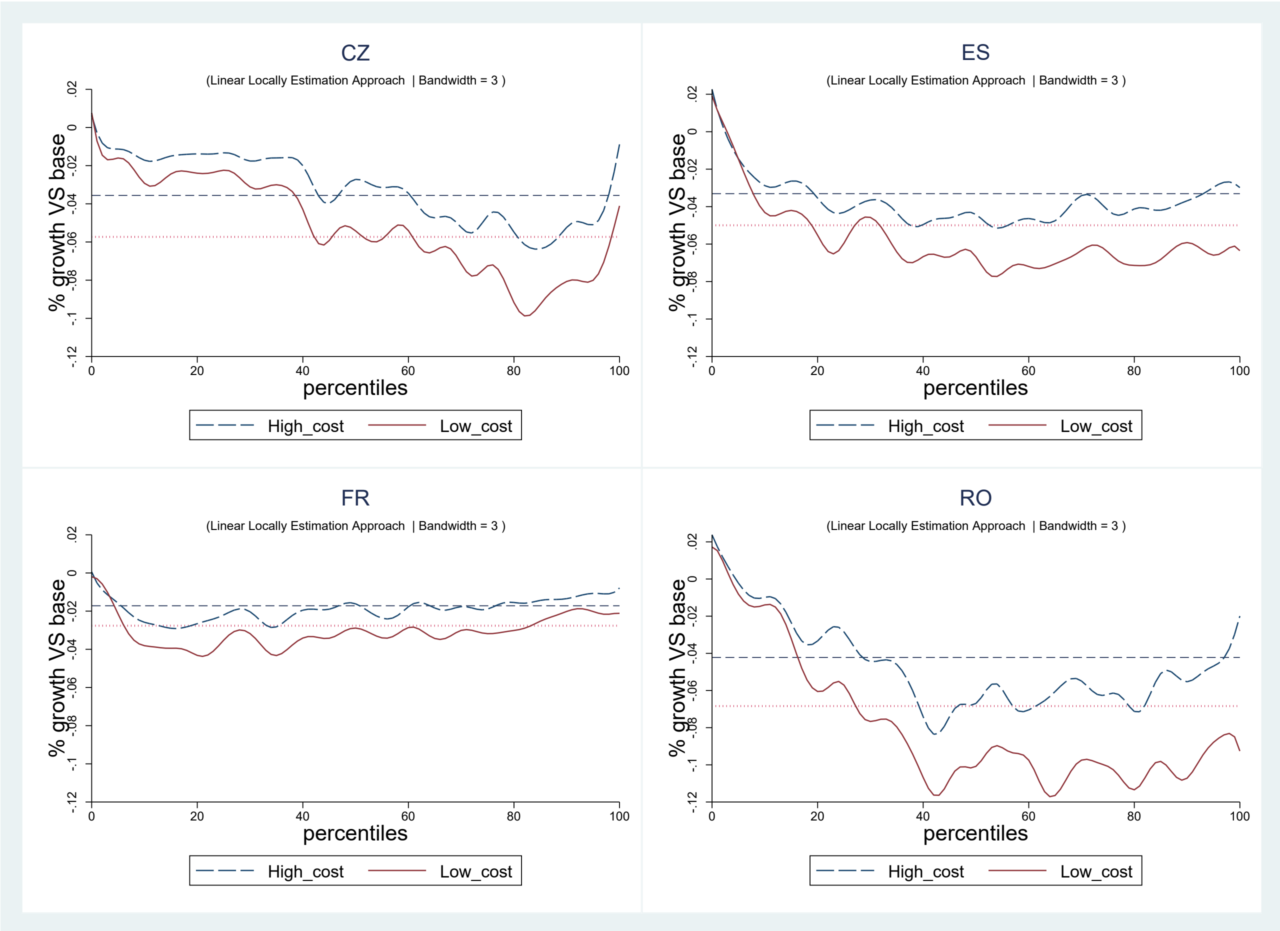
The decrease in average disposable income due to automatisation was the highest in Romania: 4.2% for the high-cost and 6.8% for the low-cost scenario. Although Romania had a lower projected employment decrease than the Czech Republic (10.3% vs.11.1% in the high-cost and 17.4% vs. 19.0% in the low-cost scenario), the higher income reduction for Romania is probably due its weaker automatic stabilisers.

Following automatisation, government expenditures on social transfers would increase by 8.3% (16.7%)[5] in the Czech Republic and by only 4.1% (8.2%) in Romania.

Figure 3 also displays changes in income at different percentiles of the baseline (pre-automatisation) income distribution. In France, changes in disposable income do not differ significantly across the income distribution. They are slightly more pronounced in the lower parts of the income distribution (although not at the very bottom income decile). This indicates that workers who are likely to lose jobs due to automatisation are present at all parts of the income distribution and slightly more concentrated at the bottom. Other countries have the opposing pattern and the income decrease is more pronounced at upper parts of the distribution. In Spain and Romania, disposable income decreases are higher than average from the 30th percentile, while in Czech Republic from the 60th percentile onwards. These opposing patterns could be due to different tax and benefit structures in the countries income decrease is more pronounced at upper parts of the distribution. In Spain and Romania, disposable income decreases are higher than average from the 30th percentile, while in the Czech Republic from the 60th percentile onwards. These opposing patterns could be due to different tax and benefit structures in the countries in our sample.

[5] In the subsequent text the first number will refer to the high-cost scenario and the second one (in parentheses) to the low-cost scenario.

Figure 3. Changes in disposable income due to automatisation



Notes: Blue long-dash and red full lines represent the percent changes in disposable income for high- and low cost automatisation scenarios. Short-dash and dotted lines represent the average effect, while the full lines represent effects at different parts of the income distribution (baseline scenario) for the high- and low-cost scenario respectively.

Source: Own calculation based on 2018 EUROMOD data

We observe an increase in inequality as measured by the Gini coefficient[6] and S80/S20 ratio[7] in all countries due to automatisation (Figure 4). This is due to the fact that newly formed income distributions after the automatisation are a result of many job losses and gains causing large shifts in the relative position of individuals and households in the income distribution. Table A1 in the Appendix compares average incomes of the deciles based on pre- and post-automatisation disposable incomes; the

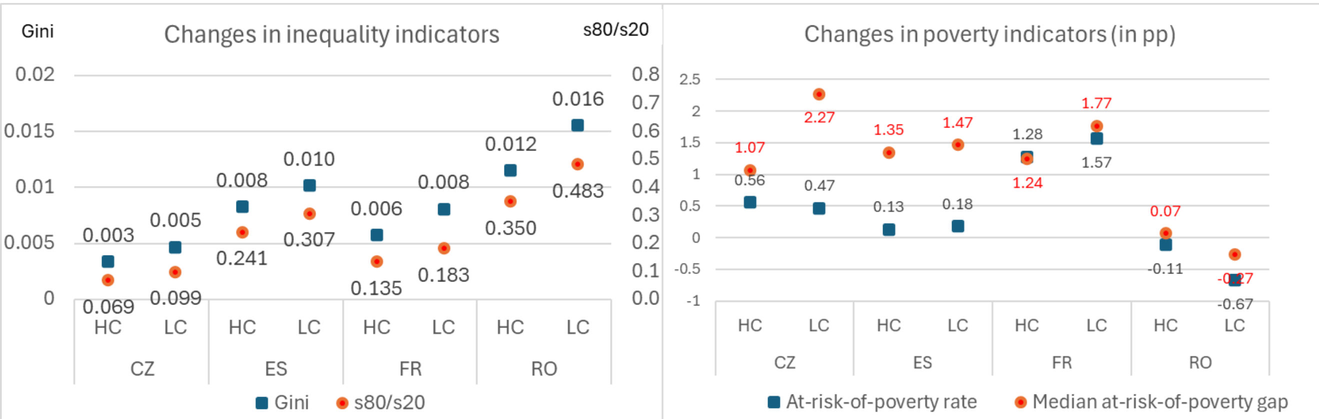
[6] Gini coefficient is defined as the relationship of cumulative shares of the population arranged according to the level of equivalised disposable income, to the cumulative share of the equivalised total disposable income received by them. It spans from 0 to 1 with values closer to 1 indicating higher inequality.

[7] Gini coefficient is defined as the relationship of cumulative shares of the population arranged according to the level of equivalised disposable income, to the cumulative share of the equivalised total disposable income received by them. It spans from 0 to 1 with values closer to 1 indicating higher inequality.

comparison shows that the income decrease is higher for those in lower parts of the distribution and lower for higher deciles. In other words post-automatisation lower deciles are worse off than pre-automatisation lower deciles and the decrease in their disposable income is more prominent than the decrease for the upper deciles.

Modest increases in inequality due to automatisation are present in all countries, and this increase is higher with a greater degree of automatisation (i.e. higher in low-cost than in high-cost scenario). The increase in inequality is the lowest in the Czech Republic and France, with the increase in Gini of 0.003 and 0.006. In these two countries the pre-automatisation inequality was the lowest (0.232 and 0.255). The increase in inequality is highest in Romania, at about 0.012 Gini points. Romania also has the highest pre-automatisation Gini - at 0.332. Similar conclusions and country differences can be observed when S80/S20 indicators are used.

Figure 4. Changes in inequality (left panel) and poverty (right panel) due to automatisation



Source: Own calculation based on 2018 EUROMOD data

On the other hand, poverty indicators show slightly different trends due to methodology of the calculation of at-risk-of-poverty line - defined at 60% of the median equivalised income. Table A1 in the Appendix shows that in the low-cost scenario in Romania, median income decreases by about 10.2%, while the decrease in the lowest decile is about 10.1%. This leads to significantly lower poverty line, at the level with the decrease in income, which in turn causes a slight decrease in poverty rates. In all other countries, the decrease of low incomes is significantly higher than the decrease of median income, leading to higher poverty rates.

4.2. Income inequality and poverty effects of the policy reform

Our reform scenario is a version of UBI: for each unemployed person we replace the current unemployment benefit (UB) with an average value of unemployment benefit in the country.[8] Automatisation increases the number of UB recipients and average benefit due to higher number of persons that are losing jobs and higher wage capacity of persons who are losing jobs. This causes an average UB to be higher in the automatisation scenarios compared to the baseline. We call this reform Universal Unemployment Benefit (UUB).

We assume no changes in expenditures for the benefit. However, in all the countries in most scenarios there is a slight decrease in the expenditures on means-tested benefits. Those who were receiving lower than average UB, and after reform would receive UUB, could no longer be eligible for some means-tested transfers (such as social assistance, child allowance, unemployment allowance, etc.) since the UB is frequently a part of the means-test. In other words, there is a slight decrease in social government expenditures after the reform with the largest decrease amounting to no more than 0.4%.

Figure 5 represents average income changes in deciles of pre-reform income distribution due to the UB reform in different scenarios. Income changes are presented as percent changes compared to pre-reform income distribution in the same scenario. There is little or no changes in the average disposable income as a consequence of the reform. This applies across countries and scenarios and is due to the design of the policy reform which effectively redistributes the amount of unemployment benefit equally to all eligible persons.

From a distributional perspective UUB would result in higher average disposable income in the first decile (and generally in the lower deciles) of the pre-reform income distribution (Figure 5). At the same time, average income for higher deciles of the income distribution decreases. Redistribution towards bottom deciles is the lowest in the baseline scenario and increases with the degree of automatisation assumed, i.e. it is higher in the high-cost and the highest in the low-cost scenario. This is due to average

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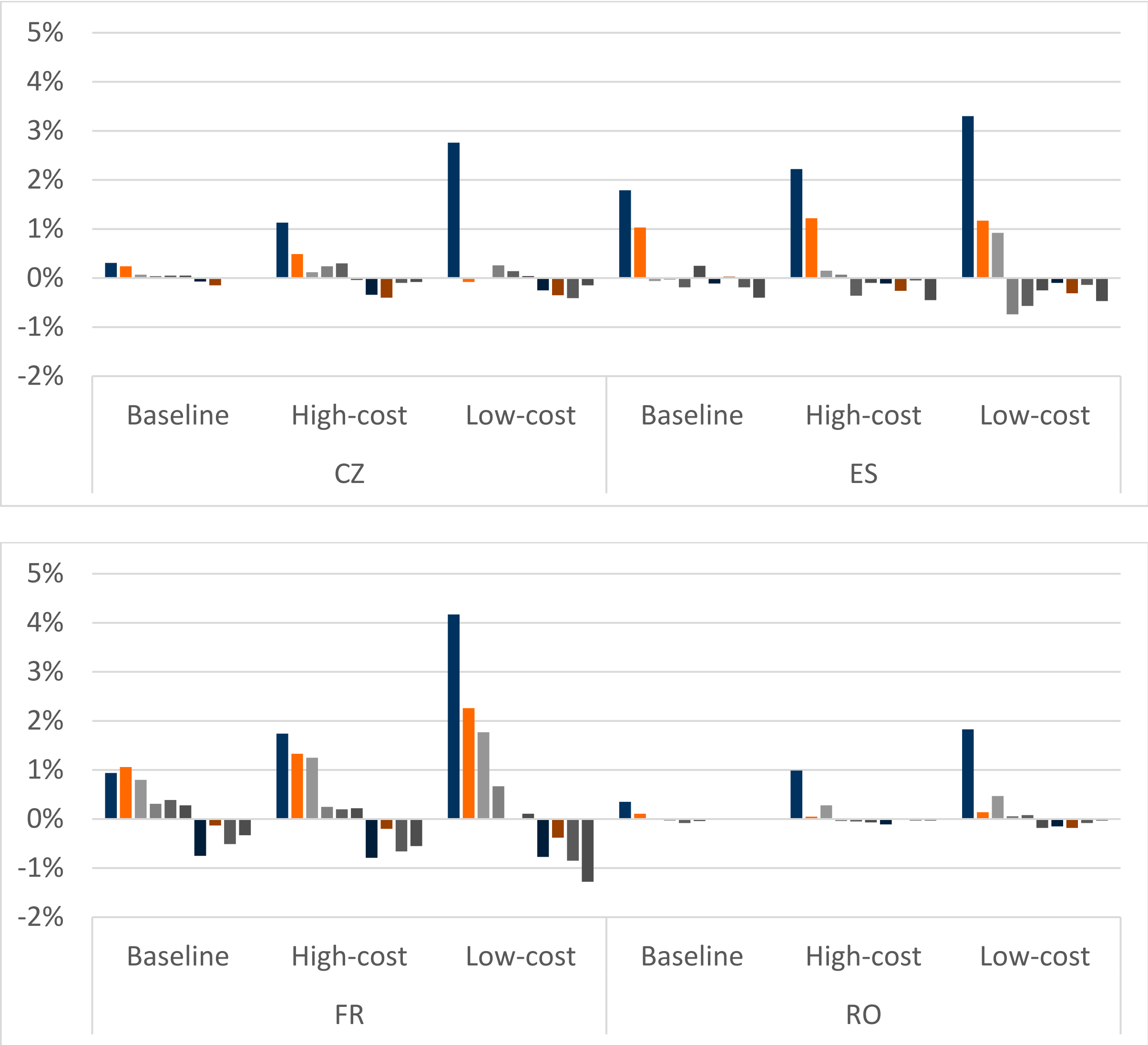
8 For Spain and France we change the design only of the main (contributory) unemployment benefit (Spain: Unemployment insurance ('Prestación contributiva por desempleo'); France: Unemployment insurance benefit (Allocation de retour à l'emploi)), which is similar to only (also contributory) unemployment benefit in Czech Republic and Romania. Additional unemployment benefits for Spain and France are unchanged (Spain: Unemployment assistance benefit ('Subsidio por desempleo') & Income Guarantee benefit ('Renta Activa de Inserción') and Temporary Unemployment Protection Programs ('PRODI, PREPARA, PAE & Subsidio Extraordinario por Desempleo'); France: Unemployment assistance Benefit (Allocation de solidarité spécifique ASS)).

UB being the highest in the low-cost scenario and the least generous in the baseline scenario. Redistribution towards to bottom decile is higher in France and Spain and lower in the Czech Republic and Romania.

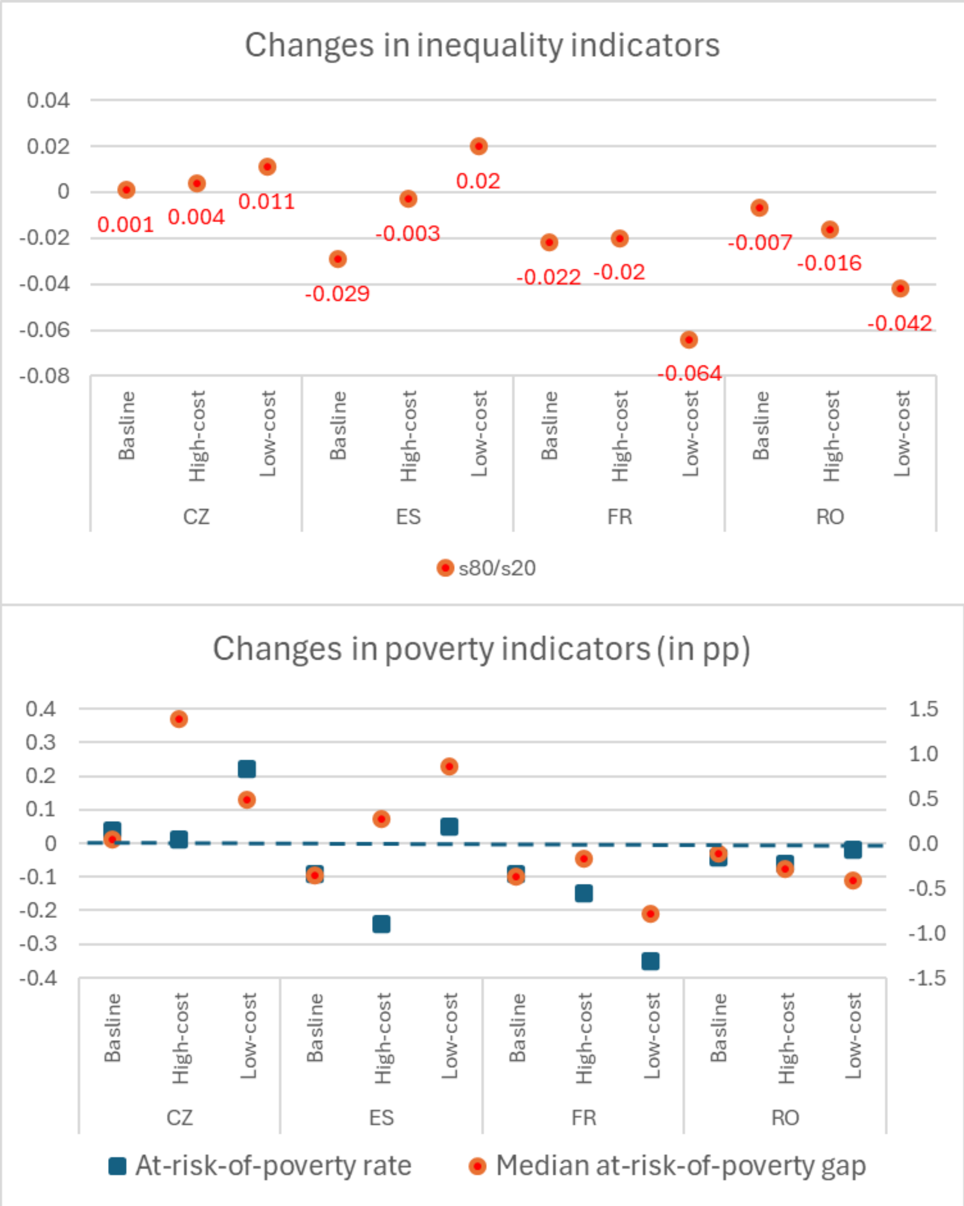
Figure 5. Changes in disposable income due to policy reform (by income decile)



Source: Own calculation based on 2018 EUROMOD data

Figure 6 presents results of changes in inequality and poverty indicators due to UB reform. Due to small changes in Gini coefficient (observed only on the 3rd or 4th decimal) we present the results in terms of S80/S20. Similar results to ones presented here for S80/20 apply for changes in Gini, however, they due to low changes they would be as visible in the graph.

Figure 6. Changes in inequality (upper panel) and poverty (lower panel) as a consequence of the UB reform



Source: Own calculation based on 2018 EUROMOD data

Results indicate mixed results across countries (Figure 6). Inequality and poverty indicators suggest lower inequality levels in France and Romania. At the risk of poverty (AROP) rate and S80/S20 are unchanged or lower in all scenarios after the reform with the highest decrease in inequality for low-cost scenario. At the same time, at the risk of poverty gap (AROP) gap is lower in both countries in all scenarios. In France and Romania proposed policy reform lowers inequality and poverty in all scenarios, while the effects are most prominent for low-cost automatisation scenario.

Results are mixed for Spain. The AROP rate and S80/S20 are lower for the baseline and the high-cost scenario, but higher for the low-cost scenario. AROP gap is higher for both high- and low-cost scenarios after the reform. Thus, UUB decreases inequality and poverty in the absence of automatisation while at higher levels of automatisation (low-cost scenario) poverty and inequality increase. For the Czech Republic, the reform brings higher levels of inequality and poverty but the effects are relatively small in size. Thus, in Spain and Czech Republic although there are positive changes in disposable income at low parts of pre-reform disposable income and negative at higher parts of pre-reform disposable income, inequality is not decreasing in the automatisation scenarios. This is due to the fact that the newly formed income distributions after the UB reform are the result of some of the unemployed receiving lower UB (if they had above average UB prior to reform) and some of the unemployed receiving higher UB (if they had below average UB prior to reform). These changes cause shifts in relative position of individuals and the new distributions are more unequal in all scenarios for the Czech Republic and low-cost automatisation scenarios in Spain.

4.3. Labour supply effects of the policy reform

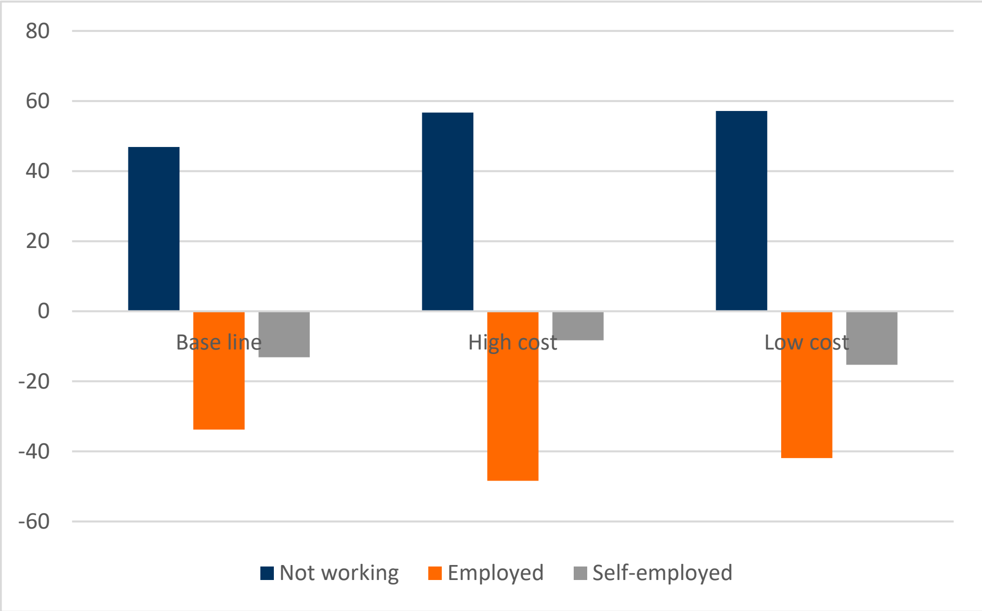
Using a discrete choice model we estimate female labour supply (details outlined in Appendix 2) and simulate the effects of providing universal amount of unemployment benefit to all single unemployed and inactive women, thereby replacing their current unemployment benefits. We decided to focus on this group given their higher elasticity of labour supply compared to couples and single men observed in the literature (Bargain & Peichl, 2016) which could bring larger effects of the policy reform. Such transfers may incentivise some women to leave the workforce, potentially increasing rates of employment discontinuation among women.

Specifically focusing on the Czech Republic, Spain, and Romania, we employ EUROMOD version 3.6.8 to model single female labour supply. Our methodology uses standard estimation techniques (refer to Table 1 in Appendix 2 for labour supply model estimates for single females in these countries). We assess welfare impacts by considering individual preferences, identifying beneficiaries, and those disadvantaged by each reform. For each country and level of transfer, we analyse changes in labour supply and corresponding household benefits or disadvantages.

Figure 7 illustrates the percentage change in the number of employed, self-employed, and non-working single women in the Czech Republic due to the policy reform, a universal unemployment benefit, across three different automatisation scenarios.

The UBI reform in the Czech Republic indicates a consistent trend of increasing the number of single women who are not working and decreasing the number who are employed. The number of self-employed women shows a slight decrease in the baseline, high, and low cost scenario. The most substantial change is seen in the decrease in employment, especially under high and low cost automatisation scenario (Figure 7 and Table A2 in the Appendix).

Figure 7. Change (in percent) number of employed/self-employed/not in working single women by cost condition due to UBI reform for Czech Republic

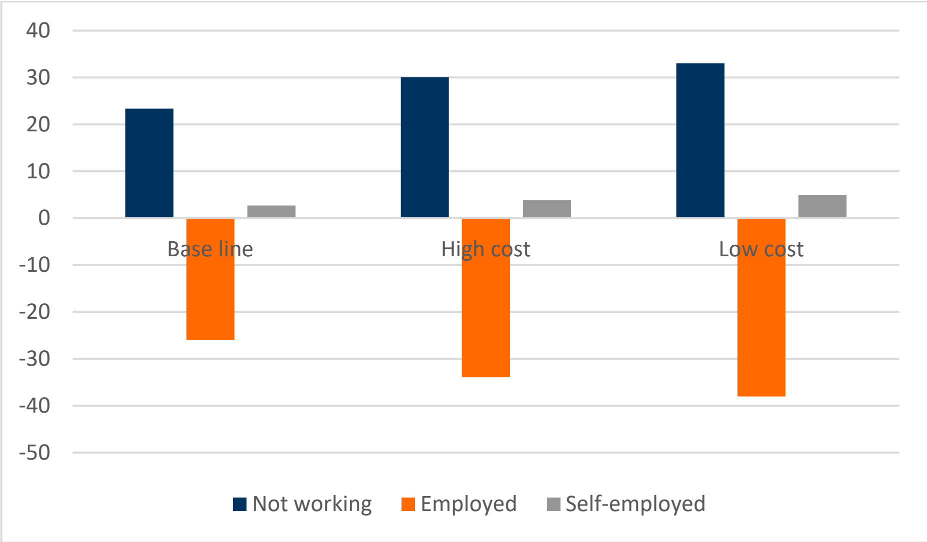


Source: Own calculation based on 2018 EUROMOD data

The Figure 8 depicts the percentage change in the number of employed, self-employed, and non-working single women in Spain due to policy reform across different scenarios.

The UBI reform in Spain results in large increase in the number of single women not working and a decrease in those employed. The number of self-employed women sees a slight increase. These trends are consistent across the scenarios with the increase in non-working and the decrease in employed being more pronounced in the high and low cost scenarios compared to the baseline (Figure 8 and Table A2).

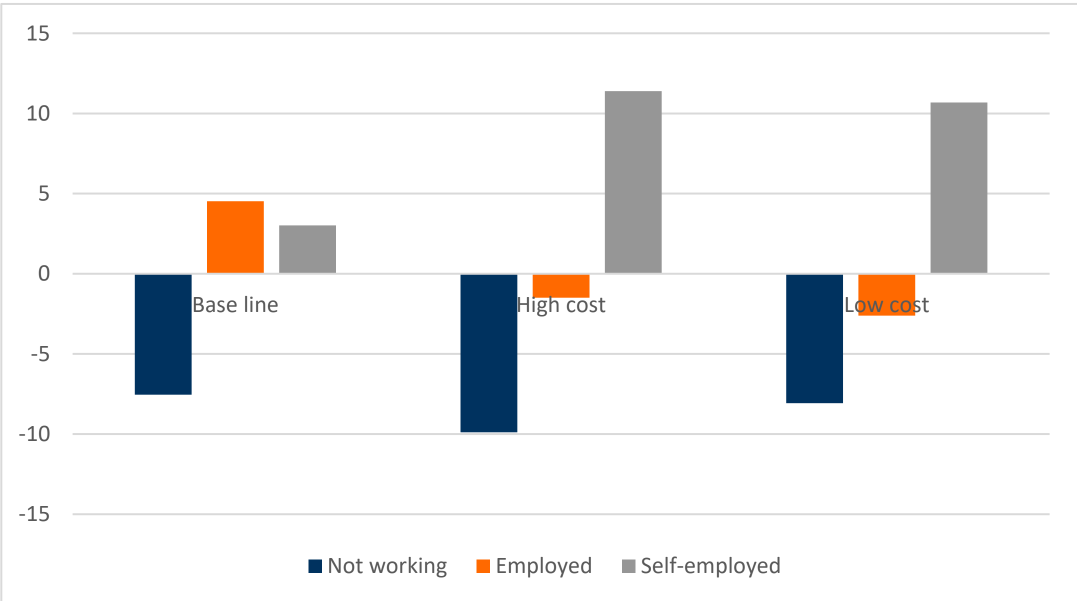
Figure 8. Change (in percent) number of employed/self-employed/not in working single women by cost condition due to UBI reform for Spain



Source: Own calculation based on 2018 EUROMOD data

The Figure 9 depicts the percentage change in the number of employed, self-employed, and non-working single women in Romania due to policy reform across different scenarios.

Figure 9. Change (in percent) number of employed/self-employed/not in working single women by cost condition due to UBI reform for Romania



Source: Own calculation based on 2018 EUROMOD data

The UBI reform in Romania results in a decrease in the number of single women not working, unlike in the Czech Republic and Spain when the number of women not working increases. There is a slight increase in the number of employed women under baseline conditions and a decrease in high and low cost conditions. Scale of changes in employment status are much smaller than compared to other two countries. Finally, there is an increase in those who are self-employed (Figure 9 and Table A2 in the Appendix). The trends indicate that UBI reform might be encouraging self-employment and reducing the number of women who are not working, with the most significant changes observed under high and low cost conditions.

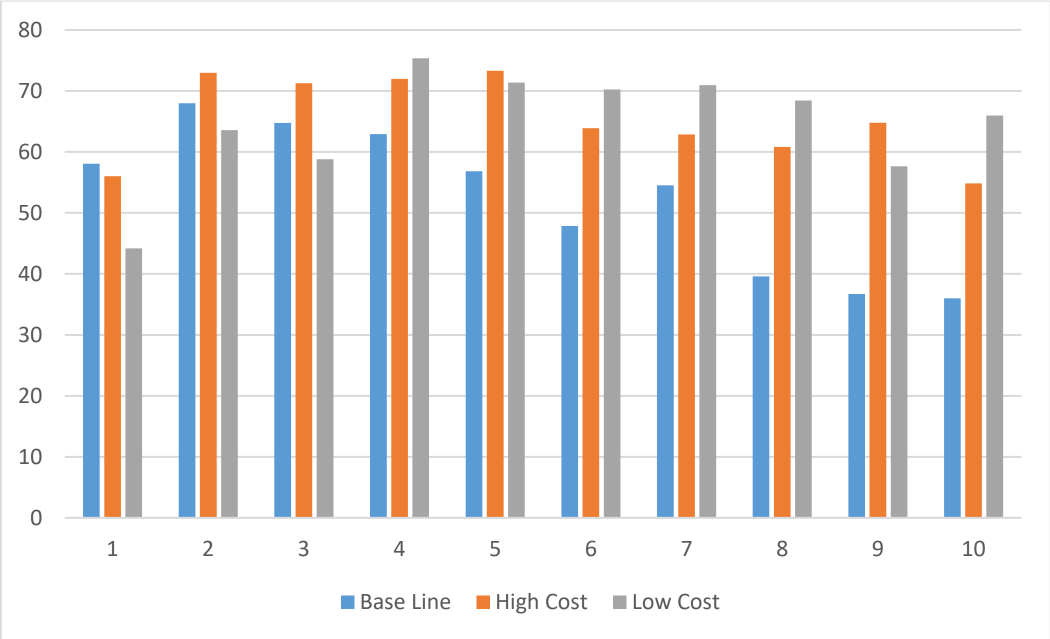
4.4. Changes in welfare following a policy reform

The study highlights significant impacts of automatisation on individual welfare. Figures 4.4.1 to 4.4.3 illustrate the share of winners in the utility function across ten scenarios (deciles 1 to 10) under three conditions: baseline, high-cost, and low-cost. Each graph represents utility function performance under different cost scenarios. The blue bar signifies the baseline condition, the orange bar the high-cost scenario, and the green bar the low-cost scenario. For each country, and decile, the graphs display three bars, each indicating the share of winners under baseline, high-cost, and low-cost conditions.

Below, we describe the findings from the reform scenario for each country:

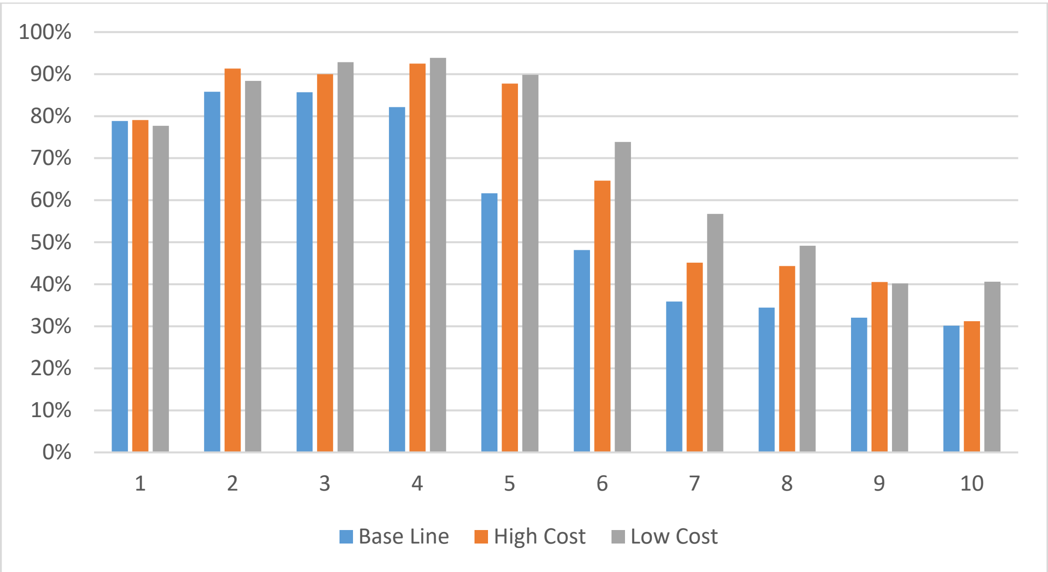
- Czech Republic (CZ): Figure 10 demonstrates that in most income deciles, the share of winners is highest under the low-cost condition (e.g., deciles 4, 6, 7, 8, and 10). In other deciles, the share of winners is higher under high-cost conditions compared to the baseline condition, except for the first income decile. The impact of cost conditions on the share of winners varies across different income deciles;
- Spain (ES): Figure 11 illustrates the share of winners in the utility function by decile (deciles 1 to 10) under baseline, high-cost, and low-cost conditions for Spain. The low-cost condition frequently results in a higher share of winners, consistently dominating all deciles except deciles 1 and 2. The baseline condition tends to perform lower or similarly compared to the other conditions.

Figure 10. Share of winners in the utility function with UBI reform with Czech Republic (CZ)



Source: Own calculation based on 2018 EUROMOD data

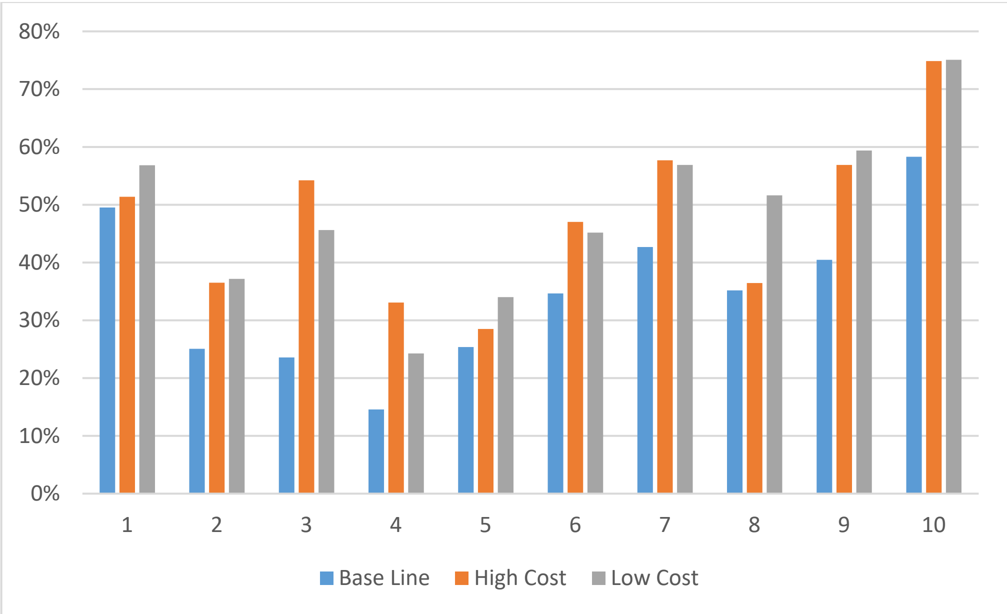
Figure 11. Share of winners in the utility function with UBI reform with Spain (ES)



Source: Own calculation based on 2018 EUROMOD data

- Romania (RO): Figure 12 depicts the share of winners in the utility function by decile (deciles 1 to 10) under baseline, high-cost, and low-cost conditions for Romania. It highlights the variability in the share of winners across these conditions. Generally, neither the low-cost nor the high-cost condition consistently dominates all scenarios. However, the high-cost condition frequently results in a higher share of winners, especially in deciles 3, 4, 6, and 7. The low-cost condition shows a higher share of winners, notably in deciles 1, 8, and 9. The baseline condition tends to perform lower compared to the other conditions.

Figure 12. Share of winners in the utility function with UBI reform with Romania (RO)



Source: Own calculation based on 2018 EUROMOD data

In summary, the graph shows how different cost scenarios influence the share of winners across ten income deciles. The low-cost scenario often results in a higher share of winners, but the effect depends on the specific income decile.

5. Conclusions

Due to megatrends, automatisation being one of them, some categories of workers are more likely to be working poor and less protected by the current social protection systems. This could exacerbate already high levels of income inequality and vulnerability. It is, therefore, important to analyse how the income distribution may evolve in different European countries under a range of potential scenarios for future changes in the job structure.

Projections regarding the impact of automation and technological change on the world of work show that country's employment trend is driven by employment shares across sectors and the relative proportion of jobs at high risk of automation in each of those sectors. We followed a model that looks at the trajectory of employment in different occupations of the European Union countries from 2018 to 2030. Based on the estimated number of jobs at the risk of automation and investment levels needed to automate routine jobs and costs of training workers in these jobs, model predicts two scenarios: a high-cost case, with slower uptake of automatisation and fewer job losses, and a low-cost one in which uptake is faster and job losses are larger.

Applying projections to the EU-SILC 2018 data we simulate changes in employment status based on the estimated job losses/job gains across different occupations and countries. The changes of employment status are based on the employment vulnerability of each job defined in the terms of employment and contract status, working time and working experience, as well as likelihood of employment estimated via probit model.

In the process of selecting the countries we decided to focus on the Czech Republic and France since they have the highest and the lowest effects of automatisation, respectively. Spain was further added to the sample as a representative of Southern European region and also due to high anticipated increase in employment by 2030 in the baseline scenario of no automatisation. Finally, we included Romania as a representative of South-East Europe and a country with the lowest increase in employment in the baseline scenario.

To assess inequality effects that result from different automatisation scenarios we use EUROMOD, tax and benefit microsimulation model for the European Union countries. An increase in inequality is observed in all countries with the lowest effect in the Czech Republic and the highest one in Romania. The role of the existing tax and benefit system is visible from the fact that although Romania had lower projected employment decrease than Czech Republic, we found higher income reduction there due to its weaker automatic stabilisers.

Static effects of the budgetary neutral policy reform - a universal unemployment benefit to all single unemployed and inactive women that replaces their current unemployment benefits - brings lower inequality and poverty in France and Romania while inequality and poverty increases for other two countries.

Behavioural effects of the policy reform are estimated using a discrete choice labour supply model. The UBI reform in the Czech Republic and Spain indicates a consistent trend of increasing the number of single women who are not working and decreasing the number of those who are employed. Reform might be encouraging self-employment in Romania and Spain. It is reducing the number of women who are not working only in Romania.

Looking at the welfare effects we observe that the share of winners is the highest in the Czech Republic and Spain in the low cost scenario, the one with the faster uptake of the automatisation. In the Czech Republic share of winners is above 60% in most deciles except for the bottom 30% of the income distribution whereas in Spain the share of winners goes over 80% but is mainly situated in the bottom 50% of the income distribution. Scenario with the slower uptake of the automatisation more frequently results in a higher share of winners in Romania.

Overall effects of the automatisation on the citizens' welfare depends on the structural characteristics of the labour market, most notably employment shares across different sectors of the economy and the proportion of jobs at risk of automation in each sector. Probability that a job susceptible to automatisation would be lost in the end is higher in case of more vulnerable circumstances like self-employment, part-time work and for a person with less working experience. In countries with more generous welfare state automatisation would bring less negative effects for poverty and income inequality.

Universal benefit income has been considered in numerous studies as an instrument that could be used to adjust the current tax and benefit to the challenges of the automatisation. In our research a version of the universal benefit income manages to encourage more self-employment among single women in Romania and Spain and to reduce the number of those who were not working before the reform but in Romania only. In France and the Check Republic reform provides work disincentives since it increases the number of single women who are not working and reduces the number of those who are employed. In terms of welfare effects, in countries with more generous welfare system there is a higher share of winners of the policy reform even in the scenario with the faster uptake of the automatisation.

Future research should look at variations of the universal income policy reforms and consider options to accommodate policy design to the labour market circumstances of the actual country and its social benefit structure. UBI could replace some other policy than unemployment benefit, like cash social assistance which exists in all European countries, and could be more generous than the proposal included in this paper. Other, more radical proposals could include the replacement of the entire social benefit system of countries under consideration with UBI policy. In that manner we will eliminate the impact of existing social protection structures on the overall results and focus on the potentials UBI provides as a safety net for workers displaced by automatisation. Also, analysis could extend to other groups such as man and women in couples.

Appendix 1

Changes in the EUROMOD files

Several variables had to be changed in the EUROMOD files to accommodate for job losses and job gains. These variables include deduction of the labour income and adjusting labour market variables so that those who lost labour income are eligible to receive simulated unemployment benefits. We impute wages for those who gained jobs, and adjust labour market variables in the data so that they are no longer eligible to receive unemployment benefits (if they were receiving them).

Specific variables are:

- **Income variables (variables yem and yse):**[9]
  - for those selected for job losses their entire gross income (yse, yem) is deducted;
  - for those selected for job gains we impute labour income to the gross income from employment variable (yem).
- **Working hours (lwh)** - participates in a number of policies depending on the country:
  - for those selected for job losses we set working hours (lhw or lower level derivation variables) to zero;
  - for those selected for job gains we set working hours (lhw or lower level derivation variables) at median working hours of the original distribution of working hours, zero working hours excluded.
- **Unemployment benefit (bun)**[10] - in the microsimulation model for all four countries unemployment benefits are partly simulated, i.e. they are conditional on reported receipt of the benefit in the EU-SILC data. France and Spain have two or more types of unemployment benefits - and these changes have been made to contributory benefits, as they are present in all countries, and most prominent in France and Spain:
  - for those selected for job losses we impute a positive value for the unemployment benefit (median value, although the condition is set on positive receipt of the bun, thus the value of imputed bun is irrelevant);

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[9] yem represents income from employment and yse income from self-employment. Additionally, variables representing lower level income aggregates are changed if they are needed for the micro-level simulations.

[10] Or lower level aggregates needed for the micro-level simulations.

- for those selected for job gains we set unemployment benefit equal to current wages.

- **Labour market status in the previous year by months**
- **Number of months spent in employment (liwmy):**
  - is set to zero for those selected for job losses;
  - is set to *12 – time in other statuses* (such as pension, inactive etc) for those selected for job gains.
- **Number of months spent in unemployment** (**lunmy**)[11] - it sets the period for which unemployment benefit can be received during the year:
  - is set to be equal to *12 – time in other statuses* (such as pension, inactive etc) for those selected for job losses;
  - and to zero for those selected for job gains.
- **Number of months receiving unemployment benefit (bunmy)** – we set this variable the same way as lunmy, the reason for this is that for most of the countries, in the simulations this does not make a big difference, and we can assume that the person is eligible for the unemployment benefit if they lose their jobs.
- **Working history (liwwh)** – it also participates in the setting level of unemployment benefit to be received:
  - remains unchanged – available for all and represent their working history.
- **income from the previous period or contributions for the unemployment benefit** (**yempv,** for Spain this variable is labelled as **bunctpc**):
  - sets the amount of unemployment benefit to be received;
  - for those selected for job losses equal to total of yem and yse person receives in their current employment (before 'job loss');
  - no changes for others, they do not full-fill other conditions now.
- **imputed income** (**yiwwg**) **–** sets the level of unemployment benefit to be received:
  - no changes, available for all.

Additionally, for countries in which these variables are relevant we modify the following variables.

[11] liwmy – number of months spent in employment (in work), lunmy – number of monts spent in unemployment.

- yemmy – number of months receiving employment income (FR, ES, RO):
    - for those losing jobs its set to zero;
    - for those fining jobs its set to 12 (assuming all work is done in wage employment).
- ysemy – number of months receiving self-employment income (FR, ES, RO):
    - for those losing jobs its set to zero.
- les – labour market status (CZ):
    - for those losing job set to unemployed (les=5);
    - for those gaining job set to employed (les=3).
- lowas – active search for jobs (CZ, FR):
    - for those losing job set to 1;
    - for those gaining jobs set to 0.
- lfs – firm size (FR, ES):
    - for those losing jobs set to 0 in accordance with the rules from DRD files;
    - for those finding jobs set to median value of the firm size in the country.
- lindi, loc – industry and occupation (FR, ES):
    - for those losing jobs set to 0 for industry and – 1 for occupation in accordance with the rules from DRD files;
    - for those finding jobs set to previous occupation or occupation most likely to increase in the future (3-associate profs, technicians) if previous occupation is missing; for industry the industry most likely to increase (6 – transport and communications). This is relevant mainly for social insurance contributions.
- lcs – civil servant (RO):
    - for those losing jobs set to zero in accordance with the DRD file;
    - for those finding jobs set to zero, as we assume they are going to find work in the private sector.

Appendix 2

We estimate a Discrete Choice Model (DCM)[12] where preferences are represented by a Box-Cox utility function incorporating income Y and leisure l:

$$U_i(Y_{ij}, l_{ij}) = \beta_y\left(Y_{ij}^{\alpha_Y} - 1/\alpha_Y\right) + \beta_{li}\left(l_{ij}^{\alpha_l} - 1/\alpha_l\right) + \varepsilon_{ij}$$

where monotonicity, resp. quasi-concavity, conditions boil down to $\beta_Y, \beta_{li} > 0$, resp. $\alpha_Y, \alpha_l < 1$.

We model preference heterogeneity by assuming

$$\beta_{li} = \gamma_{l0} + \gamma_{lz} Z_i + \theta_i$$

where Z_i is a vector of observed taste shifters (such as age, nationality, and number of children), capturing the observed preference heterogeneity, while θ_i captures the unobserved heterogeneity. We assume the θ_i are normally distributed with mean zero.

Assuming ε_{ij} are all i.i.d. distributed according to some extreme value distribution, we obtain (from McFadden) that :

$$\text{Probability } (l_i = m) = exp\left(U(Y_m, l_m)\right) / \sum_{j\in J} exp\left(U\left(Y_j, l_j\right)\right)$$

The likelihood function is the product of these probabilities with the observed m in the numerator for each individual. The likelihood function is maximised with respect to β_y, α_y, β_{li}, and α_l (and γ to take account of the observed heterogeneity). The estimated standard error e_θ gives us the magnitude of the unobserved heterogeneity. With the estimated standard error $\hat{e}_\theta$, we can compute the expected value of β_{li} as a function of $\hat{\gamma}_{l0}$, $\hat{\gamma}_{lz}$ and the estimated distribution of θ_i, conditional on the observed value of the choice, l_i.

[12] A discrete choice labour supply model is a framework used to analyse individuals' labour supply decisions by considering their discrete choices among a finite set of alternatives. These models are particularly useful for understanding how people choose between different levels of labour supply, such as working part-time, full-time, or not working at all (for more details see for example McFadden, D. 1974; Creedy, J., & Kalb, G. 2005; Hoynes, H. W. 1996; Cameron, A. C., & Trivedi, P. K. 2005.)

Table A.1 Labour supply estimate for single women

	Czech Republic	Spain	Romania
	Income(Box-Cox: 0.419) Leisure(Box-Cox: -0.532)	Income(Box-Cox: 0.372) Leisure(Box-Cox: -0.543)	Income (Box-Cox:0.289) Leisure (Box-Cox: -0.422)
Mean			
Income	2.690***	2.510***	0.345***
	-0.136	-0.0919	-0.0774
Leisure	2.411***	1.356***	1.241***
	-0.423	-0.241	-0.281
Age * Leisure	-0.0214***	0.0161***	-0.0149*
	-0.00617	-0.0046	-0.00622
Number of Children Age0-3 * Leisure	4.710***	-0.0349	n/a
	-0.965	-0.334	
Nationality * Leisure	0.079	-0.127	n/a
	-0.273	-0.111	
Standard Deviation			
Leisure	0.444***	0.00112	0.00808
	-0.0666	-0.0829	-0.199
N	905 * 7=6335	1871 * 7=13097	735 * 7=5145

Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.2 Change in the number of employed, self-employed, and non-working due to the policy reform across different automatisation scenarios

		Czech Republic	Spain	Romania
Not working	Baseline	+46.89%	+23.36%	-7.54%
	High cost	+56.70%	+30.09%	-9.89%
	Low cost	+57.16%	+33.06%	-8.08%
Employed	Baseline	-33.77%	-26.04%	+4.52%
	High cost	-48.39%	-33.95%	-1.50%
	Low cost	-41.89%	-38.02%	-2.61%
Self-Employed	Baseline	-13.12%	+2.68%	+3.02%
	High cost	-8.31%	+3.86%	+11.39%
	Low cost	-15.27%	+4.96%	+10.68%

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WeLaR is Horizon Europe research project examining the impact of digitalisation, globalisation, climate change and demographic shifts on labour markets and welfare states in Europe. It aims to improve the understanding of the individual and combined effects of these trends and to develop policy proposals fostering economic growth that is distributed fairly across society and generates opportunities for all.

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