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Navigating Technological Change: The Role of Passive Social Policies in Central and Eastern European Labour Markets

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Central and Eastern European (CEE) countries have limited research attention regarding the impact of technological change on the labour market. While existing studies offer many insights into developed countries, research on CEE countries, which have not yet achieved the level of prosperity seen in Western nations, does not take into consideration the following paradox – the existing labour force deficit and lack of technological innovation at the same time. This makes the region particularly valuable for the analysis in the context of technological change. Our study expands current theoretical understanding of the relationship between technological change and employment by examining the effects of passive labour market policies. The empirical analysis, using fixed-effects models, reveals that the overall effect of digitalization on employment is inconsistent, suggesting that the direct relationship between ICT capital and employment is not robust across specifications. This may result from the balancing of both positive and negative effects of technological change on the labour market. However, three models find a positive and statistically significant moderating effect of social protection benefits, while two showed insignificant estimates. This suggests that higher social protection can help mitigate digitalization's negative employment effects by sustaining demand and supporting jobs in non-automated sectors.

Keywords: *Technological Change; Digitalization; Employment; Social Protection Benefits.*

Introduction

Currently, there is much discussion about the implementation of cutting-edge technologies such as artificial intelligence and robotics in production. These technologies aim to automate, digitise, and optimise production processes. Previous industrial revolutions primarily impacted the industrial sector, but the expansion of digital capital significantly affects the entire economy, leading to notable impacts on the labour market.

The effects of automation on the labour market are well-researched in advanced capitalist economies but have been less analysed in Central and Eastern European (CEE) countries. The former Socialist economies, which have chosen the path of Euro-Atlantic integration, are catching up to Western European living standards, yet their economic structures still differ from countries that have not experienced communism. Automation is driven by labour costs and its shortage. CEE countries have lower labour costs compared to Western Europe but do not have the labour surplus typical of developing economies. This makes CEE and interesting region to study the uptake and effects of digitalization.

Specifically, we focus on the impact of government social policies on the relative strength of job creation versus job displacement wrought by. State social benefits may reinforce the displacement effect by not encouraging sufficient skill renewal in response to labour market changes. Conversely, social benefits may stimulate aggregate demand and overall production, thus increasing the need for labour in non-automated sectors. This raises a critical question: how do social benefits influence the relationship between digitalisation and employment?

By answering this question, we aim to expand the standard theoretical understanding of the impact of technological changes on employment by incorporating the dimension of government social policies. The theoretical and empirical justification of government decisions will enhance the understanding of the effects of technological progress and allow for the formulation of policy recommendations to strengthen positive and eliminate negative consequences.

Digitalisation is unequivocally a part of technological advancement, closely related but not synonymous with the phenomenon of automation. Although there is no universally accepted definition of automation in the scientific literature, Acemoglu and Restrepo's (2018b) designation is pertinent: "the introduction of new technologies that enable capital to be substituted for labour in certain tasks". Meanwhile, Casalino et al. (2012) understand automation as the use of control systems and information and communication technologies (ICT) in the production of goods and services, thereby reducing the need for human labour.

Digitalisation is a phenomenon closely related to, but distinct from, automation (Reis *et al.,* 2020). Digitalisation is an economic-managerial phenomenon encompassing the consequences and applications of digitisation – transformation of information from analogue to digital format. Digitalisation and automation are identified in the scientific literature as phenomena that cannot exist independently (Begic *et al.,* 2022; Marcu *et al.,* 2020; Schumacher & Sihn, 2020). In a broader sense, digitalisation can also mean automation. In production processes, the digitisation of information allows for the management of production in the digital space and, through this, the automated control of production processes (Schumacher *et al.,* 2016). Digitalisation is also used to automate service processes, such as customer consultations (Jung et al., 2018), and even bureaucratic public administration processes and decision-making (Langford, 2020). One of the ways digitalisation enables automation in production is through artificial intelligence solutions (Gangoda *et al.,* 2023). The development of artificial intelligence technologies allows systems to become more autonomous and further accelerate automation, improving work quality and accuracy (Ganz & Isaksson, 2023; Ughulu, 2022).

All of these factors reflect the technological changes shaping the world in the 21st century. The widespread adoption of ICT technologies is transforming production processes and may lead to certain types of labour becoming redundant. Therefore, this research aims to evaluate the impact of digitalization on employment at the macroeconomic level in Central and Eastern European (CEE) countries and to assess how this effect may be influenced by government passive social policies.

Theoretical Aspects of the Impact of Technological Progress on Employment

It is widely agreed that technological progress will transform the labour market, but the nature of this impact remains unclear. According to Oschinski and Wyonch (2017), technological progress leads to "creative destruction," causing the disappearance of certain jobs or employment areas due to their replacement by technology. However, they argue that automation does not necessarily lead to higher unemployment in the manufacturing sector, as it depends on whether technology and labour are substitutes or complements. Digitalisation, as part of automation, can have various effects on the labour market: it may increase unemployment as some of the workforce is replaced by technology, but new jobs may also be created due to new technologies, leaving the overall impact uncertain. The main theoretical effects of how technology can affect employment are outlined below.

The first is the **displacement** effect. The displacement effect occurs when capital replaces labour in the production process, making the workforce redundant (Acemoglu & Restrepo, 2018b). Clearly, the displacement effect negatively impacts employment as technology replaces jobs, making part of the workforce redundant.

The second effect is the **productivity** effect (Acemoglu & Restrepo, 2018b). With the adoption of advanced technologies in the production process, increased productivity reduces costs, allowing for a reduction in the price of products, which in turn leads to an increase in demand. Consequently, there is a need to increase production volumes, which requires an increase in non-automated labour. Thus, the productivity effect positively impacts employment. Technological progress can also improve a product or service, resulting in increased demand and a need for labour (Oschinski & Wyonch, 2017).

The third effect is the **reinstatement** effect, whereby automation in the production process creates new tasks that are not yet automated and need to be performed by the workforce (Acemoglu & Restrepo, 2018b). This also positively impacts employment, as the newly created tasks must be performed by the workforce. Alternatively, automation can ease work and improve labour productivity by performing certain tasks, allowing the workforce to focus on other tasks that technology cannot handle (Oschinski & Wyonch, 2017).

The fourth effect is the **capital accumulation** effect, which occurs when labour is needed to maintain new technologies (Acemoglu & Restrepo, 2018b). This also creates new jobs and positively impacts employment. Furthermore, according to Oschinski and Wyonch (2017), technology does not necessarily perfectly replace the workforce but may create new jobs to supervise the technology.

Another effect is the **residual** effect, which means that after automating a certain production process, some tasks remain for the workforce, but these tasks require higher skills, and thus the workers with those skills are likely to earn more (Bessen *et al.,* 2022).

Summarising, the impact on employment depends on the strength of these effects. If the displacement effect is stronger, automation will negatively impact employment. Otherwise, automation may even increase employment. These effects can reduce the impact of technology on overall employment (Oschinski & Wyonch, 2017). Based on these arguments, technology might improve the quality of life without causing mass unemployment as observed during previous industrial revolutions.

The impact of automation on the labour market depends on the relative strength of positive and negative effects. The displacement effect will be stronger in cases where a large part of the labour market performs routine work (Acemoglu & Restrepo, 2019), as well as when there is a skills mismatch (Acemoglu & Restrepo, 2018a). This can occur when the pace of automation is very rapid, and workers cannot adapt their skills to market needs (Acemoglu & Restrepo, 2018a). Moreover, high labour costs can encourage businesses to invest in automated technologies that can displace the workforce (Dechezleprêtre *et al.,* 2021; Dinlersoz & Wolf, 2023). Automation can also be driven by labour shortages, where investment in capital equipment would allow for the continuation of production expansion (Danzer et al., 2020). Conversely, if new technologies create new tasks and the labour market flexibly responds to the changing skills needs, the productivity effect will be stronger, and automation will positively impact employment (Acemoglu & Restrepo, 2018a, 2019; Kromann *et al.,* 2020). Thus, the productivity effect is more likely in countries with high wages and labour shortages, while the displacement effect is more likely in countries with low wages and labour surpluses (Huettinger *et al.,* 2020).

The impact of automation on the labour market is almost unexamined in Central and Eastern European countries. This region has different characteristics compared to the most analysed developed Western European or North American countries and is also unlike the developing economies of Eastern and Southeast Asia. Firstly, the level of labour costs in these countries is still lower than in Western countries but is rapidly increasing and higher than in developing economies. According to Eurostat data, in 2020, the average hourly labour cost in the 27 European Union (EU) countries was 28,4 euros. All Central and

Eastern European countries had average hourly labour costs below the EU average, ranging from 6,6 euros in Bulgaria to 20,7 euros in Slovenia. In contrast, all Western European countries had average hourly labour costs above the EU average. For reference, some developing non-EU countries also reported very low average hourly labour costs, such as Turkey (4,2 euros) and Serbia (6,8 euros). Secondly, similar to Western Europe, Central and Eastern European countries experience a shortage of labour, which developing economies do not. Similarities between Western European and Central and Eastern European (CEE) countries in terms of labour shortages are illustrated by job vacancy rate data. According to Eurostat, the average job vacancy rate across the 27 EU countries was 1.8%. Some CEE countries, such as Czechia and Latvia, reported higher rates, while Ireland and Italy had lower rates. No clear geographic trend was observed in the European Commission data regarding the share of companies indicating labour shortages (Eurofound, 2024). High labour costs and labour shortages should drive automation, but labour costs in Central and Eastern European countries are still lower than in the West. Furthermore, Central and Eastern European countries have a less generous social security system and a relatively educated workforce. All this indicates that the relationship between positive and negative effects of automation is unclear. Therefore, econometric analysis of Central and Eastern European countries would help understand the impacts of automation in a different context, thus expanding the knowledge in the field of economics.

Review of Empirical Studies

The multifaceted impact of automation on employment has been extensively explored across different sectors and skill levels, revealing complex dynamics influenced by the relative strength between displacement and productivity effects. Notably, automation tends to adversely affect low-skilled workers and those engaged in routine tasks, presenting a higher risk of job displacement (Arntz *et al.,* 2017; Pajarinen & Rouvinen, 2014; Pouliakas, 2018). Conversely, high-skilled workers and those in-service sectors, particularly in roles requiring social interactions, generally face lower risks (Pouliakas, 2018). This differential impact is also reflected in sector-specific variations, with the manufacturing, agriculture, and commerce sectors experiencing higher automation risks (Diaz & Grau Ruiz, 2020; Csefalvay, 2020).

Empirical analyses further substantiate these observations, as evidenced by Oschinski and Wyonch (2017), who noted a significant shift towards non-routine cognitive jobs in the Canadian labour market, aligning with the Routine-Based Technological Change hypothesis. This shift suggests an adaptive workforce moving towards sectors less susceptible to automation, such as social services and ICT (Charnoz & Orand, 2017). However, the displacement effect remains pronounced in routine job sectors, with substantial job losses projected in certain industries (Graetz & Michaels, 2018; Dengler & Matthes, 2018).

Regionally focused studies, such as those by Mann and Püttmann (2021) in the U.S., reveal nuanced impacts where automation correlates positively with employment in non-routine sectors, yet shows a reduced effect in areas with prevalent routine jobs. This complexity is reflected in robotization studies in Germany (Dauth *et al.,* 2017), which highlight a non-uniform impact across industries and regions, suggesting a context-dependent nature of automation's effects on employment.

Empirical studies also analyse the effects of technological change on other labour market indicators. Research has found conflicting effects on overall wage levels. For example, Pouliakas (2018) identified a negative impact on wages in the European Union, whereas Graetz and Michaels (2018) reported the opposite effect in their analysis of 17 advanced economies. Meanwhile, Chiacchio et al. (2018) did not find consistent results.

However, at a more disaggregated level, empirical studies consistently show that technological change benefits highly skilled workers, while the wages of middle- and low-skilled workers may decline (Gravina & Foster-McGregor, 2020; Dauth *et al.,* 2017; Pham *et al.,* 2018). Additionally, empirical evidence supports the notion that technological change tends to enhance labour productivity, particularly among highly skilled workers (Goos, 2018; Sanders & Ter Weel, 2000; Violante, 2008).

Overall, while automation presents a substantial displacement risk, particularly for routine and low-skilled employment, its overall impact on the labour market is moderated by sectoral differences and the adaptive responses of the workforce. This nuanced perspective is crucial for developing policies and strategies to mitigate adverse effects while maximizing the benefits of technological advancements in the workplace.

The Role of Social Benefits in the Relationship between Digitalisation and Employment

Scientific literature agrees that automation will lead to increased inequality between high- and low-skilled workers (Correa *et al.,* 2019; Goos *et al.,* 2021; Maliar *et al.,* 2022), who may need to seek social support from the state. Kurer & Hausermann (2022) have found that workers negatively affected by automation will expect more passive social policies, such as unemployment benefits, rather than active social policies like retraining or education.

The threat of automation, therefore, may lead to voters favouring politicians promising greater redistribution and support for industries struggling due to automation (van Hoorn, 2018). Automation will create winners and losers (Graetz & Michaels, 2018), so politicians, aiming to stay in power, will try to implement policies relevant to their voters: the winners of automation will seek further technological progress, while the losers will seek government intervention to mitigate the undesired economic consequences (Gallego & Kurer, 2022).

A generous national social welfare system may discourage workers from retraining and adapting to the changed technological environment, making withdrawal from the labour market an attractive alternative. This is confirmed by many empirical studies, which have found a negative impact of social benefits on employment (Pereira & Andraz, 2015a, 2015b; van der Ploeg, 2003). However, other empirical studies suggest a positive impact of social benefits on employment through greater inclusion and productivity (Osabohien *et al.,* 2020; Ramdwar *et al.,* 2020).

The positive impact of social benefits on employment is usually observed through the Keynesian model of economic fluctuations, where government intervention can stimulate aggregate demand, leading to increased overall production and employment. The positive impact of social benefits on aggregate demand is also supported by empirical studies, confirming Keynes' theoretical model (Arestis *et al.,* 2021; Eichhorst *et al.,* 2010).

Although the Keynesian model is usually used to explain short-term economic fluctuations, these effects can also be observed in medium- and long-term phenomena, including those caused by automation. As mentioned, technology can not only replace labour but also increase product demand and labour demand, expressed through the productivity effect (Acemoglu & Restrepo, 2018b). However, to the best of the authors' knowledge the literature has not examined cases where the productivity effect is driven externally, for example, by stimulating aggregate demand through social benefits.

Therefore, the role of social benefits in technological progress is twofold. The prevailing belief is that social benefits reduce incentives for retraining, making workers less likely to return to the labour market. On the other hand, it allows displaced workers to maintain purchasing power, increasing aggregate demand and creating a need for new jobs. Given this potential dual effect of social protection benefits, further empirical analysis is required to determine the direction of this impact.

To evaluate the effects of digitalization on employment while accounting for the influence of social protection, a macroeconomic econometric study is conducted to identify relationships and trends relevant to the economies of CEE countries.

Research Hypotheses

As discussed in the previous section, the impact of automation on a country's labour market can be varied. If the displacement effect is stronger than the productivity, reinstatement, capital accumulation, and residual effects, it is likely to lead to decreasing employment. Conversely, if the strength of the effects is opposite, automation is expected to increase employment. It is also possible that the overall effect of these factors at the national level is balanced, resulting in no significant impact of automation on labour market indicators. Empirical studies show that, in many cases, when evaluating all economic sectors, no significant impact of automation on labour market indicators is identified. However, Central and Eastern European countries have different characteristics, so a different effect can be expected. Therefore, the impact of automation on individual sectors is expected to be different. Considering these ambiguities, we present the following two mechanisms and hypotheses that follow.

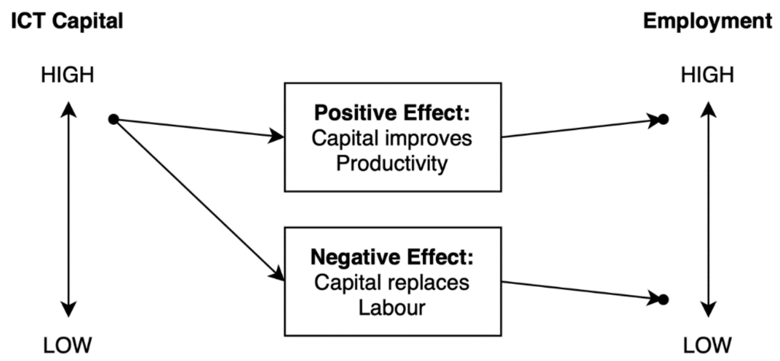

Figure 1. Causal Graph for the Relationship between ICT Capital and Employment

The effect of ICT Capital on Employment is negated by contradictory forces we call *negative effect* and *positive effect*. The negative effect suggests that high levels of ICT Capital replace Labour, because Capital can perform tasks generally delegated to Labour, which in turn has a negative effect on employment. The positive effect proposes that high levels of ICT capital improve productivity and reduce costs, which leads to higher demand for Labour. That is, the displacement effect in CEE countries is of similar strength to the productivity and other effects (*see* Figure 1). Taking this into consideration, the final effect of digitalization is expected to be low and, therefore, statistically insignificant. Although wage levels in Central and Eastern Europe are lower than in Western Europe, the labour shortage, which limits production expansion, is similar, leading to increased production and demand for new jobs due to automation. On the other hand, digital capital will replace some workers, creating jobs in some sectors and losing them in others, with the overall effect likely to be insignificant (Hutschenreiter *et al.,* 2022; Mann & Puttmann, 2021). Existing empirical studies show contradictory results; for example, in Germany, no impact of automation on overall employment was found (Dauth *et al.,* 2017), while a broader geographical context shows a negative impact of automation on employment (Carbonero *et al.,* 2020; Chiacchio *et al.,* 2018). As a result, we construct the following hypothesis:

H1: *Digitalization does not have a direct impact on overall national employment.*

Furthermore, we propose that Social Protection Benefits moderate the effect of ICT Capital on Employment in the following way. High levels of ICT capital and Social Protection Benefits stimulate the Aggregate Demand, which results in the increased levels of production, and in turn, higher levels of employment. On the other hand, a combination of increasing levels of ICT Capital and low levels of Social Protection Benefits have a negative effect on the levels of production through the same mechanism. As a result, employment suffers. The causal graph (see figure 2) explains the proposed relationship. ICT capital not only can replace labour but also increase product demand and labour demand, also through the stimulation of aggregate demand (Acemoglu & Restrepo, 2018b). The empirical evidence shows that social protection benefits can stimulate aggregate demand (Arestis *et al.,* 2021; Eichhorst *et al.,* 2010), therefore we expect that social policy could mitigate the adverse effects of technology on labour. The hypothesis follows:

H2: *The interaction of digitalization and social protection expenditures has a positive impact on national employment.*

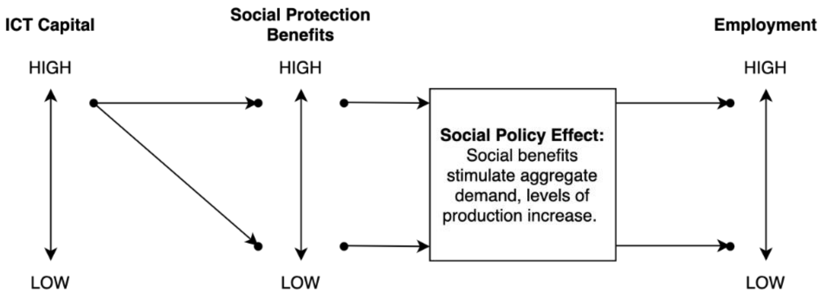

Figure 2. Causal Graph: ICT Capital, Social Protection Benefits, and Employment

Research Methodology and Empirics

Research Data. The empirical study analyses 11 Central and Eastern European countries: Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia. After the collapse of the Soviet Union and the Warsaw Pact, these countries have chosen the path of Euro-Atlantic integration, resulting in institutional structures similar to Western European countries. Despite rapid convergence, these states still lag behind Western European neighbours economically but are much more advanced than non-EU Eastern and Central European countries. As mentioned earlier, these characteristics distinguish this region from other countries in studying the impact of automation on the labour market and are therefore important for the empirical study.

This empirical study explores the beforementioned relationship between digitalization and employment that is not caused by short-term fluctuations, aiming to assess long-term trends. Therefore, the study employs data from 1995 to 2020, subject to data availability[1].

Dependent Variable: Number of Employed People (EMP). This is one of the most important indicators for assessing the consequences of automation on the labour market. The total number of employed people indicates the overall demand for labour. Observing this indicator over time shows how overall employment in the country changes. By linking this variable to automation, it can be determined whether automation reduces or increases overall national employment. This indicator is used in many empirical studies assessing the impact of automation on employment (e.g., Dauth et al. (2017), Qin et al. (2022), Carbonero et al., 2020; Chiacchio et al., 2018; Dauth et al., 2017; Dengler & Matthes, 2018; Mann & Püttmann, 2021). The data for this indicator is taken from the EU KLEMS database.

Independent Variable: Amount of Information and Communication Technology (ICT) Capital (KICT): This variable measures the amount of digital capital, evaluated using the chain-linked method. The variable includes three types of digital capital: computing equipment, communication equipment, and computer software and databases. As this study aims to assess the effects of digitalization, ICT capital is an appropriate choice as it represents the overall stock of digital equipment in the economy. According to Dauth et al. (2017), ICT capital can perform some tasks previously carried out by labour, making it a relevant indicator of the role of digitalization in the production process. This variable has been widely used in empirical studies to assess the effects of technological change on the labour market (e.g., Charnoz & Orand, 2017; Chiacchio *et al.,* 2018; Dauth *et al.,* 2017; Graetz & Michaels, 2018). Among possible digitalization indicators, ICT capital is preferred as it captures long-term investments in technology rather than short-term digital adoption trends, also it is an appropriate variable for analysing digitalization in a macroeconomic context because it captures the cumulative stock of digital assets at the economy-wide level. The data for this indicator is taken from the EU KLEMS database.

Moderator: Social Protection Benefits (SocProtBen).

This variable measures the overall expenditure on social protection in a country. It is expressed in euros per inhabitant at constant 2010 prices to account for differences in country size and eliminate inflation effects. This variable is used to test hypothesis H2, examining whether social protection expenditure influences the relationship between digitalization and employment. Prior empirical studies (e.g., Arestis *et al.,* 2021; Pereira & Andraz, 2015a, 2015b) have used total social protection expenditure to analyse its economic effects. The choice of euros per inhabitant, rather than total expenditure as a share of GDP, allows for a more precise evaluation of the generosity of the system at the

[1] The dataset includes observations for 11 CEE countries over the 25-year period. Due to data limitations, the total number of observations in the regressions varies from 211 to 245 observations.

individual level, making it a suitable measure for cross-country comparisons. Data source: Eurostat.

Economic Control Variables:

- **Real Gross Domestic Product (GDP).** To assess the overall impact of automation on the national labour market, the country's GDP calculated by the chain-linked method (2015) and measured in millions of euros is used as a control variable. This indicator comprehensively evaluates the country's economic development and fluctuations, which also affect labour market indicators. Therefore, this indicator allows the assessment of labour market changes independent of automation, but due to overall economic development. The impact of real GDP on employment has already been assessed in empirical studies (Filip, 2015; Soylu *et al.,* 2018; Zielinski, 2018) and a positive relationship has been found, so a positive relationship is also expected in this study.
- **Share of the Manufacturing Sector in the Economy (ManShare).** To assess the overall impact of automation on the labour market, an indicator showing the share of the manufacturing sector in the national economy is included. This indicator is calculated by dividing the value-added created by the manufacturing sector (C category activities according to NACE Rev. 2 classification) by the GDP. The theoretical analysis mentioned that the manufacturing sector is less resistant to automation, so the size of this sector can affect the dynamics of the entire national labour market. Empirical studies suggest that the growth of the manufacturing sector contributes to economic and employment growth (Karami *et al.,* 2019), so a positive impact of this variable on labour market indicators is expected.
- **Trade Openness (TradeOp).** The dynamics of the labour market can be affected by the country's openness to foreign trade. A more open economy is more susceptible to economic changes in foreign countries, which can affect employment and other labour market indicators. This indicator is calculated by dividing the sum of the country's imports and exports by the GDP. Economic openness can affect the labour market in two ways. On the one hand, increasing export opportunities stimulate employment and raise wages (Bhat & Beg, 2023; Jiang *et al.,* 2022; Rashidi, 2022). On the other hand, imported goods can displace local producers and negatively affect the labour market, although the effects may vary across sectors (Bloom *et al.,* 2019; Li & Sun, 2023). In evaluating Central and Eastern European countries, economic openness is expected to have a positive impact on labour market indicators.
- **Expenditures on Research and Experimental Development (RDEXP).** This variable shows the country's investment in technological potential, which can also affect national employment. Research and experimental development can contribute to the growth of workforce qualifications, increase productivity, and improve the quality of goods and services. Empirical studies have found that investments in R&D have a positive impact on employment, wages, and productivity, although the effect depends on the sector (Bogliacino *et al.,* 2011; Perrot *et al.,* 2013; Piva & Vivarelli, 2017). A positive macroeconomic impact is expected.

Demographic-Regulatory Control Variables:

- **Share of Younger Population (YoungPop):** Studies show that younger people are more likely to adopt new technologies and adapt their qualifications to new technological requirements. Younger people also form a significant part of the labour supply, affecting employment and other labour market indicators. This empirical study uses the share of the population aged 25-44. Empirical studies show that a larger share of the young population can positively impact productivity and employment (Shimer, 2001). The share of the younger population is expected to have a positive impact on employment.
- **Share of Population with Higher Education (TertEd):** The theoretical analysis mentioned that qualified workers are more resistant to automation, so a larger share of the educated population can affect labour market indicators. This empirical study uses the variable for the share of the working-age population (aged 25-64) with higher education. It is suggested that higher education leads to higher employment, wages, and better working conditions, confirmed by empirical studies (Negara, 2018; Soviz & Chavooshi, 2019). However, the mass expansion of higher education can devalue its importance (Yang, 2024). The share of the population with higher education is expected to have a positive impact on employment.
- **Labour Market Regulation Index (LMR):** The empirical study in this article uses the Fraser Institute's labour market regulation index. This index includes aspects of labour market regulation such as the possibility and duration limitations of fixed-term employment contracts, the minimum wage level, flexibility in hiring and firing, flexibility in wage determination, working time restrictions, dismissal costs, military service requirements, and restrictions on employing foreigners (Gwartney, 2023). The higher the index value, the more flexible the labour market regulation. Labour market regulation is variously measured in empirical studies, and its impact on the labour market is assessed differently, with no definitive conclusion on whether the impact is positive or negative (Fernandez-Villaverde, 2017; Tjong & Schmillen, 2019). In Central and Eastern Europe, more flexible regulation is expected to positively impact employment.

The selected control variables account for various aspects of economic development (GDP, trade openness, manufacturing share), demographic trends (share of the young population, share of individuals with tertiary education), and regulatory factors (labour market regulations). However, the relationship between ICT Capital and employment may also be influenced by additional factors. Many global shocks, such as financial crises, are largely reflected in GDP fluctuations, while trends in globalization are captured through the trade openness variable. Government taxation policies could also have an impact, but we expect their effects to be partially incorporated into the labour market regulation index, which reflects broader policy influences on employment and economic activity.

Structure of the Dataset. This empirical study examines data from 11 countries over a period of 26 years, forming a panel data set. According to Gujarati and Porter (2009), panel data allow for the observation of variations across multiple countries over time while accounting for differences between them. Moreover, panel data enable a larger sample size, making the data more informative. Such data are suitable for analysing the dynamics of change and behavioural patterns. Digitalization affects the labour market over time; therefore, to assess the effects of this dynamics across multiple countries, a panel data set is required. Accordingly, econometric methods specific for panel data analysis are used to assess the impact.

Selection of Econometric Method. When conducting panel data regression analysis, the choice of model depends on assumptions regarding the significance of the intercept term across cross-sectional units (in this case, countries) and time periods (in this case, years). If it is assumed that all countries have the same intercept term at all time periods, then the data from different years and countries can be pooled into a single dataset, and regression coefficients can be estimated using the pooled ordinary least squares (OLS) method. However, if it is assumed that the intercept terms differ, then either the fixed effects or random effects method is applied.

If cross-sectional units have different intercept terms, the case fixed effects model can be used. In this model, the regression equation includes N−1 dummy (binary) variables representing the cross-sectional units. Then, using the least squares dummy variable (LSDV) method, the regression equation parameters are estimated (Baltagi, 2021; Gujarati & Porter, 2009). The case fixed effects method is appropriate when the goal is to assess the relationship between variables over time within different groups. This approach allows for a separate equation to be estimated for each entity, making it possible to analyse how the independent variable is related to the dependent variable across all groups.

If time periods have different intercept terms, the time fixed effects model is applied, incorporating T−1 dummy (binary) variables representing different time periods into the regression. Using the least squares dummy variable method, the parameters of the regression equation are estimated (Baltagi, 2021; Gujarati & Porter, 2009). The time fixed effects method is suitable when the aim is to evaluate the relationship between variables across cross-sectional units, meaning that the focus is on understanding differences between different entities rather than changes over time.

Although the fixed effects method allows for the evaluation of differences between countries and years, Gujarati and Porter (2009) note that a large number of dummy variables can significantly reduce the degrees of freedom, potentially leading to multicollinearity issues and making it difficult to estimate the effects of other time-invariant variables.

If the intercept term differs across cross-sectional units, the random effects method can also be applied. In this case, the intercept term is treated as a random variable with a residual error component (Gujarati & Porter, 2009). When estimating regression equation parameters using the random effects method, the generalized least squares (GLS) method must be used (Gujarati & Porter, 2009; Wooldridge, 2009).

Finally, endogeneity issues must be taken into consideration. The theoretical literature explains the causal mechanisms through which technological change can affect employment (e.g., Acemoglu & Restrepo, 2018b; Bessen et al., 2022). However, there is also the possibility that labour shortages encourage firms to invest in technological advancements and increase their ICT capital stock (Graetz & Michaels, 2018; Carbonero et al., 2020; Chiacchio et al., 2018). To address the issue of reverse causality, the independent variable lagged by one year is used in the regression analysis. Since the dependent variable cannot influence the value of the independent variable from the previous year, reverse causality is not a concern.

Research Contribution

The literature review revealed that the effects of technological change have been predominantly analysed in advanced Western economies, while Central and Eastern European (CEE) countries have mostly been studied in the context of broader European trends. This study contributes to the literature by focusing exclusively on CEE countries, which have distinct economic structures and labour market characteristics compared to Western economies. The theoretical foundation builds upon the conflicting mechanisms of technological change, including the negative displacement effect and the positive effects of productivity, reinstatement, capital accumulation, and residual, as suggested by Acemoglu & Restrepo (2018b) and Bessen et al. (2022). This study posits that, at the aggregate level, these opposing forces may offset each other, potentially leading to an overall low or insignificant effect of digitalization on employment.

However, a key contribution of this research is its evaluation of the moderating role of passive social policies. While previous empirical studies have examined the impact of social protection on employment (e.g., Arestis *et al.,* 2021; Pereira & Andraz, 2015a, 2015b), the existing literature lacks an assessment of how passive social policies influence the relationship between ICT capital and employment. This study addresses this gap by incorporating social protection benefits as a moderating variable, measured in euros per inhabitant. Unlike broader social expenditure indicators, this approach reflects the generosity of the welfare system and its potential influence on workers' willingness to remain in the labour market.

By examining these macroeconomic effects, emphasizing the unique characteristics of the CEE region, and integrating the moderating role of social protection benefits, this study advances the literature on the effects of technological change on labour market (Graetz & Michaels, 2018; Dengler & Matthes, 2018; Mann & Puttmann, 2021; Dauth *et al.,* 2017; Carbonero *et al.,* 2020; Chiacchio *et al.,* 2018).

Empirical Analysis

All models are estimated using the fixed effects regression models. Within-unit fixed effects model allows us to estimate the desired dimension of variance in our panel data – variation in employment within CEE countries over time (Kropko & Kubinec, 2020). We use the following procedure: we start by estimating the models using only the dependent and independent variables, and then, add economic controls only. The final models include all control variables – that is, both economic and demographic-regulatory confounders. This procedure is used to ensure the consistency of the results across regression models and that the missing values in some of the controls don't affect the results significantly. Regression equations are presented below.

The first generalized model tests hypothesis 1:

1) $EMP_{it} = \beta_0 + \beta_1 \cdot KICT_{it-1} + \beta\boldsymbol{X} + \sum_{i=1}^{N-1} \delta_i C_i + u_{it}$

The second model tests hypothesis 2:

2) $EMP_{it} = \beta_0 + \beta_1 \cdot KICT_{it-1} + \beta_2 \cdot SocProtBen_{it-1} + \beta_3 ModBen_{it-1} + \beta\boldsymbol{X} + \sum_{i=1}^{N-1} \delta_i C_i + u_{it}$,

where EMP represents the number of employed people in thousands over time and across cases, KICT stands for ICT capital in millions of national currencies, SocProtBen represents the state's expenditure on social protection in euros per inhabitant, X – is a vector of above-described confounders, ModBen is the interaction between ICT capital and Social Protection Benefits. Associated beta coefficients and the error term are presented in the model. Case dummies are also included in the regression equations.

Descriptive Statistics of Variables. European countries (Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia) for the period of 1995-2020. Before the empirical analysis is performed, here are some initial insights about the data. Most of the observation on the dependent variable (EMP) are concentrated in the range of 600,000 – 2,500,000 people with a median of 2,173,000 people, minimum of 570,000 and maximum of 16,404,000 people (see Table 1 for detailed descriptive statistics). Due to nonlinear nature, high range of values and concentration of observations in certain areas, we use a natural logarithm of independent variable (KICT) for the empirical analysis in this article. The vast majority of observations for the natural logarithm of independent variable are located in the range of 6.25 and 8.75 with minimum and maximum values of 4.86 and 14.76, and median of 8.1.

Table 2 presents the correlation matrix of the variables used in the empirical research to identify potential multicollinearity issues among the right-hand-side variables. Most correlations exhibit moderate strength, indicating a low risk of multicollinearity. However, the correlation between ICT capital and GDP is strong, with a coefficient of 0,7710. Similarly, the correlation between ICT capital and the manufacturing share is also strong, at 0,6070. Finally, there is a strong correlation between social protection benefits and R&D expenditure, measured at 0,7729. These correlations are taken into consideration when testing the regression models.

Table 1

Descriptive Statistics

Variable	Mean	Median	St. deviation	MIN	MAX
EMP	4100,14	2173,41	4323,98	569,66	16403,7
KICT	171336,80	3306,99	444373,47	129,06	2562670,54
GDP	88048,53	44658,15	96640,21	9241,90	514873,20
TradeOp	104,67	98,00	37,10	25,14	188,81
YoungPop	28,65	28,40	1,35	25,50	31,60
TertEd	22,57	21,80	8,42	8,70	44,10
SocProtBen	1941,70	1831,27	950,86	369,78	5235,67
ManShare	15,70	15,00	3,77	7,64	25,28
LMR	6,83	6,81	0,79	4,66	8,60
RDEXP	0,93	0,80	0,47	0,35	2,56
ln_EMP	7,85	7,68	0,97	6,35	9,71
ln_KICT	9,08	8,10	2,49	4,86	14,76
ln_GDP	10,94	10,71	0,91	9,13	13,15
ln_SocProtBen	7,45	7,51	0,52	5,91	8,56

Table 2

Correlation Matrix

ln_EMP	ln_KICT	ln_GDP	ln_SocProtBen	TradeOp	YoungPop	TertEd	ManShare	LMR	RDEXP	
1,0000	0,6960	0,9267	-0,1593	-0,3168	0,2894	-0,5027	0,3560	0,4080	-0,2406	ln_EMP
	1,0000	**0,7710**	0,2593	0,0793	0,2495	-0,4041	**0,6070**	0,3326	0,1818	ln_KICT
		1,0000	0,1779	-0,0724	0,3427	-0,4137	0,4884	0,4451	0,0128	ln_GDP
			1,0000	0,5605	0,1526	0,1660	0,3980	0,0419	**0,7729**	ln_SocProtBen
				1,0000	0,1031	0,5292	0,2595	0,3001	0,5323	TradeOp
					1,0000	-0,3899	0,3830	0,2968	0,1044	YoungPop
						1,0000	-0,1724	-0,0978	0,3269	TertEd
							1,0000	0,1011	0,4589	ManShare
								1,0000	-0,2038	LMR
									1,0000	RDEXP

The table 3 presents different regression analysis models. First, hypothesis H1, that automation does not affect national employment, is tested. Then, hypothesis H2, that the interaction between automation and social benefits positively affects employment, is evaluated. According to model (1), there is no statistically significant relationship between ICT capital and employment. This supports hypothesis H1, which suggests that automation does not have a direct impact on employment. However, when control variables are included (model (3) and model (4)), the coefficient becomes negative and statistically significantly different from 0. This suggests that economic, demographic, and regulatory variables confound the relationship between ICT capital and employment, revealing a previously hidden negative effect. Furthermore, the variables Real GDP and Manufacturing Share were eliminated from the models due to their high correlation with ICT capital. Model (5) includes only the remaining economic variables and confirms a negative and statistically significant relationship between ICT capital and employment. However, when demographic and regulatory variables are included (model (6)), the relationship becomes statistically insignificant. This suggests that the previously observed negative relationship may have been influenced by multicollinearity among the explanatory variables rather than reflecting a robust effect of ICT capital on employment. Overall, these findings fail to provide strong evidence of a consistent negative relationship between ICT capital and employment, partially supporting hypothesis H1. Additionally, the magnitude of the estimates is relatively low, suggesting that the ambiguous results regarding the impact of digitalization on employment may be explained by the balancing effects of both positive productivity and negative displacement effects, mentioned in the literature review. However, the ambiguous results suggest that another factor may influence the relationship between ICT capital and employment. Therefore, hypothesis H2 is tested.

Table 3

Results of Regression Analysis

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
const	7,812*** (0,05604)	9,499*** (0,2535)	5,823*** (0,3877)	5,059*** (0,4468)	8,037*** (0,08737)	7,549*** (0,1341)	5,916*** (0,2895)	5,506*** (0,3437)	9,252*** (0,2598)	8,811*** (0,4586)
ln_KICT_1	0,0007283 (0,006179)	-0,1432*** (0,03275)	-0,07300*** (0,01051)	-0,03556*** (0,008780)	-0,03432** (0,01093)	-0,0004114 (0,01176)	-0,09080** (0,03372)	-0,02309 (0,03652)	-0,05877 (0,03844)	-0,007367 (0,05444)
ln_SocProtBen_1		-0,2660*** (0,03527)					-0,3235*** (0,03032)	-0,2984*** (0,02801)	-0,2357*** (0,03400)	-0,2399*** (0,04326)
ModBen_1		0,02381*** (0,003573)					0,01030** (0,004006)	0,006072 (0,004456)	0,01069** (0,004594)	0,007738 (0,006625)
ln_GDP			0,2372*** (0,04233)	0,2853*** (0,04691)			0,4000*** (0,03502)	0,3911*** (0,03116)		
TradeOp			-0,0005915* (0,0002659)	-0,0007583** (0,0002806)	0,0006619** (0,0002475)	0,0005336* (0,0002858)	-0,0005264* (0,0002395)	-0,0005493** (0,0002266)	0,001262*** (0,0002982)	0,0006694* (0,0003023)
ManShare			0,005564*** (0,001674)	0,006287*** (0,001605)			0,002848** (0,001244)	0,003207** (0,001306)		
RDEXP			0,03297* (0,01635)	0,02321 (0,01559)	0,02738 (0,02236)	-3,711e-05 (0,02045)	0,04900*** (0,01441)	0,02255 (0,01286)		
YoungPop				0,005166* (0,002786)		0,01444*** (0,003033)		0,004208 (0,002500)		0,01175** (0,003911)
TertEd				-0,0007126 (0,0009642)		0,002583* (0,001170)		0,002037** (0,0007927)		0,005560*** (0,0009219)
LMR				-0,03166*** (0,005362)		-0,03556*** (0,006171)		-0,02247*** (0,004822)		-0,02807*** (0,006613)
n	245	220	242	223	242	223	220	211	220	211
Adj. R^2	0,0001	0,1232	0,3001	0,4564	0,1026	0,2281	0,6302	0,7218	0,2368	0,4009

Dependent Variable: ln_EMP. (Standard errors are presented in parentheses)
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Models (2), (7), and (8) evaluate the hypothesis H2 regarding the interaction effect between ICT capital and social benefits. When only the social benefits variable and the interaction between social benefits and ICT capital are included (model (2)), a negative relationship is found between ICT capital and employment. The size of social benefits has a negative impact on employment, but the interaction term has a positive impact on employment. Therefore, the marginal effect of ICT capital on employment is calculated as $-0.1432 + 0.02381 \times$ ln_SocProtBen_1. This implies that ICT capital only has a positive impact on employment if the logarithm of last year's social benefits exceeds 6. In other words, if social benefits are relatively low, then automation negatively affects employment. However, as social benefits increase, the effect becomes positive.

A similar result is obtained when economic control variables are included (model (5)). The direct impact of ICT capital is negative and statistically significant, but the moderator coefficient is positive and statistically significant. Therefore, the marginal effect on employment is $-0.09080 + 0.01030 \times$ ln_SocProtBen_1. The impact of ICT capital becomes positive only when the logarithm of social benefits exceeds 8.82. According to the descriptive statistics, none of the examined countries have reached such a level of social benefits.

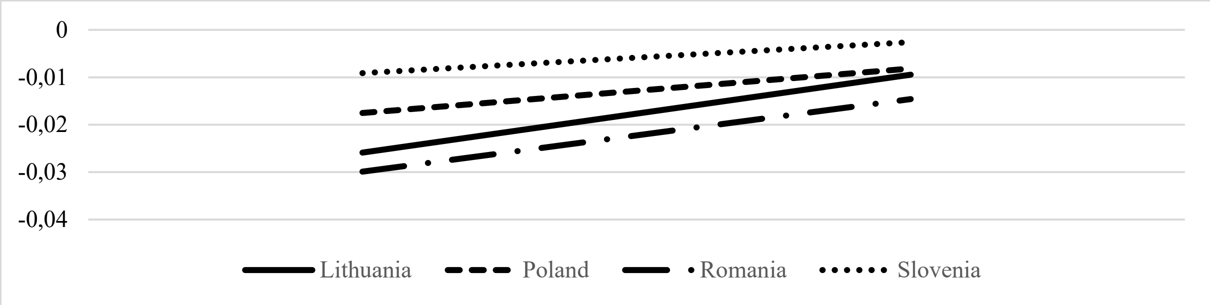

Figure 3. Marginal Effects of ICT Capital on Employment, Taking Into Consideration Social Protection Benefits

The graph (figure 3) visualizes the marginal effects for selected countries from different regions (Lithuania from the Baltic States, Poland from the Visegrad Group, Romania from the countries that joined the EU in 2007, and Slovenia from the former Yugoslav countries). The graph shows the change in the marginal effect between the minimum and maximum values of social benefits in each country. It is evident that the effect approaches zero as the value of social benefits increases, but in all examined countries, the effect remains negative. However, the effect size is small. On average, a 1% increase in ICT capital reduces employment by between 0.02% and 0.03%. While the effect is statistically significant, it is not large and decreases further as the value of social benefits increases.

When demographic and regulatory control variables are included (model (6)), statistical significance disappears. Finally, models (9) and (10) exclude variable GDP, Manufacturing Share and R&D Expenditure, due to potential multicollinearity. The key effects regarding moderating effect remain the same.

Finally, models (9) and (10) exclude the variables GDP, Manufacturing Share, and R&D Expenditure due to potential multicollinearity. The key effects related to the moderating effect remain unchanged. The results of the empirical study partially confirmed hypothesis H1, suggesting that ICT capital is not statistically significantly related to employment. Additionally, the effect becomes negative when moderators or control variables are included.

Models (2), (7), and (9) confirm the hypothesis H2, that the interaction between social benefits and ICT capital has a positive and statistically significant impact on employment. This implies that as social benefits increase, the marginal effect of ICT capital on employment also increases. In other words, state support helps workers remain in the labour market, even though an increase in ICT capital might otherwise have a negative impact.

Discussion

Theoretical Insights. The empirical study in this article found that increasing social benefits reduces the marginal impact of automation on employment. This can be explained through several channels. First, as mentioned earlier, social benefits provide an income source during the transition period, allowing the workforce to adapt their qualifications or spend time looking for work. Social benefits can also facilitate labour mobility, enabling workers to relocate to places where their skills are in demand. Another effect may be through more favourable opportunities to start a business, receiving income during the early stages of business creation. However, the most important impact is through the growth of aggregate demand. Without social benefits, workers who lose their jobs due to automation would be unable to purchase goods and services, leading to a decline in aggregate demand for goods and services. However, social benefits allow these individuals to participate in the goods market, albeit to a lesser extent. Increasing aggregate demand increases the need for production capacity, including in non-automated sectors. This means that maintaining aggregate demand through social benefits can later open up employment opportunities in non-automated jobs. Given the period analysed in this dissertation's empirical study, which spans over 20 years during which Central and Eastern European countries were catching up with Western European countries, and social benefits were one of the most important labour market policy measures, this explanation is most suitable.

Thus, this study shows that at the theoretical level, the relative strength of effects depends on aggregate demand, which can be influenced by state fiscal policy. Therefore, to fully understand the consequences of automation on employment, it is necessary to evaluate not only the potential for displacement but also the impacts on the overall market, which can amplify or mitigate the marginal effects. This article contributes to the existing theory not only by empirically assessing the impact of automation on Central and Eastern European countries, but also by revealing the importance of social and labour market policies and their impact on the effects of automation. This study adds that when evaluating the relative strength of effects, it is necessary to consider the effects of aggregate demand, which can be stimulated by the state. It also empirically finds that passive labour market measures can help mitigate the negative impact of automation.

Practical Insights. Based on our result we propose assistance to socially vulnerable groups as a way to mitigate the negative consequences of automation. Examples, of such assistance include protecting low-income residents by regulating the minimum wage (Goos, 2018) or creating a social safety net to finance minimum living needs (Díaz & Grau Ruiz, 2020). However, the scientific literature suggests introducing universal basic income (Csefalvay, 2019; Lukina *et al.,* 2016): a regular and unconditional payment to every member of society (Reed & Lansley, 2016). In the context of automation, UBI would allow workers displaced from the labour market to maintain an income source (Hoynes & Rothstein, 2019; Reed & Lansley, 2016; Tsvirko, 2020). With an unconditional income source, people would have fewer constraints on retraining or starting a business (Hoynes & Rothstein, 2019; Pateman, 2004). Essentially, the introduction of universal basic income would be a compensatory mechanism for people who lost their jobs due to automation, reducing income inequality between the winners and losers of the fourth industrial revolution, and minimizing the risk of self-employed individuals being excluded from the social security system (Csefalvay, 2019).

Although universal basic income would simplify the bureaucratic social security system and replace many existing types of social benefits (Csefalvay, 2019), critics argue that it could be too heavy a burden on state finances (Tsvirko, 2020). On the other hand, new sources of income could be found with the development of automation. For example, taxing robots (Diaz & Grau Ruiz, 2020; Kovacev, 2020; Pham *et al.,* 2018), with the collected revenues used not only to finance conventional social benefits like unemployment benefits but also to fund universal basic income. Additionally, to maintain labour competitiveness in the factors of production markets, it is recommended not to tax labour more than capital (Goos, 2018). However, robot taxation raises certain challenges. Firstly, there should be a very clear legal definition of a robot (Kovacev, 2020). Additionally, taxing robots might reduce investments in innovation and lead to the relocation of production to jurisdictions with more favourable taxation (Kovacev, 2020). It is clear that social benefits are a relevant measure to mitigate the consequences of automation, as shown by the empirical study in this article. Therefore, financing this system will require robot taxation, which will also be necessary for Central and Eastern European countries.

On the other hand, the mitigating effect of social benefits is based on retrospective data analysis. Essentially, this shows the relationships that existed in the past. The analysis period was long enough, so it can be expected that this effect will last for at least another decade. However, the development of exponential technologies might accelerate the pace of automation to the extent that social benefits will no longer be able to stimulate aggregate demand, and the structure in which CEE countries lived will no longer be able to cope with the negative consequences of automation. In that case, universal basic income will be one of the alternatives to ensure the level of welfare, and its financing from robot taxation will be bearable for state finances. However, universal unemployment, even with a guaranteed income source, can have negative consequences. Firstly, there will be a sense of injustice in society, where some members do not work but receive income. Additionally, the unemployed might experience psychological problems, an excess of free time, leading to socially harmful behaviour. Finally, universal basic income would undermine society's autonomy from politicians, posing a threat to the quality of democracy.

The above points suggest a need for other alternatives instead of universal basic income to ensure a livelihood for workers displaced by automation while avoiding mass unemployment. One such possibility – the notion of the employer of last resort (Fullwiler, 2007; Tcherneva, 2012; Wray, 2000, 2007). Although this idea was created as a fiscal stimulus measure to stabilize short-term economic fluctuations, it could be adapted to address long-term problems caused by automation. Its main idea is that the government should create jobs to meet social needs or infrastructure projects to eliminate involuntary unemployment. Essentially, it would be similar to universal basic income but received for work in created jobs. This suggests that automation may lead to a situation where artificial market intervention is necessary to ensure employment. On one hand, this may lead to economic inefficiencies, but on the other hand, it provides the luxury of engaging in activities that improve the quality of life. However, these long-term trends might gradually emerge in CEE.

Conclusions

The analysis of scientific literature reveals that automation is a pertinent and diversely explored phenomenon in theoretical and empirical research. Various perspectives on this phenomenon and its effects underscore the need for a more detailed analysis.

Theoretically, five effects have been identified through which automation might impact the labour market. The first is the displacement effect, where capital substitutes labour, reducing the influence of the workforce. The second is the productivity effect, where technological advancements decrease production costs and increase demand for products, thereby increasing the demand for labour in non-automated tasks. The third is the reinstatement effect, where automation creates new tasks that are performed by the workforce. The fourth is the capital accumulation effect, where an increase in capital intensifies the demand for labour to manage this capital. The fifth is the residual effect, where after automating the production process, tasks remain that require a highly skilled workforce. The impact of automation on the labour market depends on the relative strength of these effects. The displacement effect is likely to be stronger in regions with a surplus of labour and low wages. However, the productivity effect will be more pronounced in countries with high wages and labour shortages. From this perspective, the countries of Central and Eastern Europe, which have lower wages than Western Europe but no labour surplus, demonstrate an unexplored relative strength of these effects.

Most empirical studies have identified a negative impact of automation on employment in the manufacturing sector. However, the overall level impacts vary. Research agrees that automation will increase the wage disparity between highly and lowly qualified workers. Yet, a clear macroeconomic impact on the overall wage level has not been established. Empirical studies do not take into account the potential impacts of active and passive labour market policies on the relationship between automation and labour market indicators.

An empirical study conducted in Central and Eastern European countries assessed the impact of digitalization on employment. Hypothesis H1, which posits that digitalization does not directly affect overall national employment, was partially supported. The estimates vary across specifications. In the baseline model without controls, the estimated coefficient on ICT capital was 0,0007 ($p > 0{,}1$), suggesting that digitalization has no significant effect on employment, as expected in the hypothesis. However, after including control variables, the coefficient shifted to values between -0,07 ($p < 0{,}01$) and -

0,0004 (p > 0,1), indicating that accounting for economic, demographic, and regulatory factors reduces the estimated effect. The statistical significance remains inconsistent, suggesting that the direct relationship between ICT capital and employment is not robust. This could be attributed to the balancing of both positive and negative effects of technological change on the overall labour market.

Hypothesis H2, which suggests that the interaction between digitalization and social security expenditure has a positive effect on national employment, was partially supported. While a positive and significant interaction is found in three models, two models yield insignificant estimates. The estimated coefficient on the interaction between ICT Capital and Social Protection Benefits is positive, ranging from 0,02 (p < 0,01) to 0,006 (p > 0,1). This suggests that higher social protection benefits can mitigate the negative effects of digitalization on employment. Accounting for social protection benefits alters the marginal effect of ICT capital on employment. For example, in Romania, when social protection benefits were 369,8 euros per inhabitant, a 1% increase in ICT capital led to a 0,03% decline in employment. However, when social protection benefits increased to 1632,1 euros per inhabitant, the decline was only 0,015%. These results provide no evidence that social protection benefits discourage labour market participation. On the contrary, they help sustain overall demand and support employment in non-automated jobs.

This research contributes to a better understanding of the effects of technological change in Central and Eastern Europe. These countries have primarily been analysed in the contexts of other European countries, with many studies focusing on specific sectors or regions rather than overall macroeconomic trends. In general, the effects estimated in this study align with the findings of Carbonero et al. (2020), who analysed 41 economies and identified a negative effect of technological change on employment. However, Chiacchio et al. (2018) found a positive effect of ICT capital on employment, though their analysis was conducted at the NUTS2 regional level. These contrasting findings and the ambiguous results of this study may be explained by sectoral differences. For instance, Graetz and Michaels (2018) found a positive effect of technological change on employment in the service sector but a negative effect in manufacturing, while Dauth et al. (2017) found no overall impact on employment in Germany but reported a negative effect in the manufacturing sector. To the best of the authors' knowledge, the moderating effect of social protection benefits has not been extensively studied. It is well known that passive labour market policies may discourage individuals from adapting to new technologies and remaining in the workforce (Pereira & Andraz, 2015a, 2015b; van der Ploeg, 2003). On the other hand, social protection can provide income support during transition periods and facilitate job creation in other sectors (Osabohien *et al.,* 2020; Ramdwar *et al.,* 2020). This research supports the positive role of social protection, demonstrating that it can be used to mitigate the negative effects of digitalization.

Considering the results of the empirical study, it is recommended to monitor whether the development of automation is outpacing the growth of overall demand stimulated by social benefits. Gradually moving towards taxing robots to fund retraining and social benefit costs is advisable. Caution is urged against the swift introduction of universal basic income; instead, alternative opportunities should be explored to maintain the incomes of those displaced from the labour market.

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