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REFORMING LABOUR TAXATION: ADDRESSING THE EMPLOYMENT EFFECTS OF TECHNOLOGICAL PROGRESS

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Abstract
As technological progress rapidly transforms the labour market, traditional labour taxation systems face a double challenge: declining tax revenues and the growing need to finance social security systems. This study analyses the impact of labour income tax cuts on employment in the context of technological progress using a general equilibrium model calibrated for the European Union economic zone. The simulation results show that labour income tax cuts have a positive effect on employment, especially at lower levels of automation, but that this effect weakens with increasing levels of automation. The study reveals that while tax cuts stimulate economic activity and partly compensate for the loss of tax revenue through increased consumption and investment, there is a persistent negative impact on government revenue. This points to the need to find alternative sources of tax revenue to ensure the sustainability of public finances in the context of technological progress.

Keywords: *labour income tax, technological progress, employment, public finance.*
JEL Codes: *H24, O33, E62.*

Introduction

Technological progress in the 21st century has reached unprecedented proportions, fundamentally changing the entire structure of the economy, including the labour market. Digitalisation, automation, and artificial intelligence are particularly accelerating these changes, rapidly transforming jobs (Di Battista et al., 2023).

While technological progress has historically created more jobs than it has destroyed, as noted by Hotte (2022), the current situation is of greater concern. Frey and Osborne's (2013) study revealed that the US labour market will undergo radical changes due to the rapid introduction of automation and new technologies, which could fully automate 47% of jobs and potentially threaten another 13%. Today, low – and medium-skilled jobs are the most vulnerable and the easiest to automate, while the demand for high-skilled jobs is growing (Bonekamp and Sure, 2015). Zhou et al. (2019) forecast that by 2049, artificial intelligence could replace around 35.8% of current jobs.

These labour market developments put public finances under double pressure. On the one hand, tax revenues are being squeezed by rising structural unemployment and the proliferation of new forms of work, which allow for aggressive tax planning. On the other hand, there is increasing pressure on government spending, with a growing need for investment to retrain the workforce, while the growing number of socially vulnerable groups poses additional challenges to social security systems, which are already under pressure from an ageing population. This situation is particularly problematic given that labour income taxes represent a significant share of total tax revenues in EU countries (OECD, 2024).

The impact of technological progress on the labour market and public finances has attracted significant academic attention. Acemoglu and Restrepo (2018) have developed a theoretical framework to analyse the impact of automation on the labour market, assessing both the potential for job losses and job creation.

Bonekamp and Sure (2015) used empirical research to highlight the importance of worker skills in the context of technological transformation. Zhang (2019) examined how the tax system affects wage inequality between workers with different skills. Acemoglu et al. (2020) investigated the potential of tax system reforms to increase employment. Guerreiro et al. (2022) proposed a model of an efficient tax system, separately assessing the taxation of routine (easily automated) and non-routine workers. Jacobs and Thuemmel (2023) examined the interaction between optimal income taxation and education policy in the context of technological change.

While the need for tax system reforms in the context of technological progress has received attention in the academic literature, there is a lack of empirical studies that quantify the effectiveness of tax cuts on employment. Existing studies mainly focus on analysing the impact of technology on the labour market (Bonekamp and Sure, 2015; Acemoglu and Restrepo, 2018) or on specific reforms of the tax system, such as taxation of robots (Gasteiger and Prettner, 2022; Thuemmel, 2022).

The main objective of this study is to empirically assess the feasibility and employment implications of a labour tax reform, taking into account different levels of automation in the economy. This research applies a general equilibrium model that allows for a comprehensive assessment of the impact of changes in the tax system on macroeconomic variables, including employment, at different levels of automation. The model is calibrated for the European Union economic area. The results not only confirm the positive impact of reducing labour taxation on employment but also reveal a key challenge: a significant reduction in tax revenues. This indicates directions for future research into alternative sources of tax revenue. The significance of the research is twofold. First, the model developed provides a new methodological approach to studying the interaction between labour taxation and technological progress. Second, the results provide an empirical basis for tax policy decisions, helping to identify the most effective scenarios for labour taxation reforms.

The article consists of three sections. The literature review analyses previous research on the impact of technological progress on employment and tax system reforms in this context. The methodology section presents a general equilibrium model and research methodology. The results section presents the simulation results and discusses their implications for tax policy. The study is limited to an analysis of labour taxes and their impact on employment in the context of technological progress, excluding other taxes.

Literature review

Artificial intelligence (AI) and automation technologies have the potential to significantly impact the labour market and revolutionise almost all professions (Frank et al., 2019). Recent studies show that artificial intelligence, robotics, and automation have the potential to transform 60% of all jobs in developed economies (Manyika et al., 2017). It is predicted that by 2030, artificial intelligence could automate up to 300 million jobs globally, particularly impacting routine and manual tasks (Bangash et al., 2024). For example, in China alone, it is projected that AI could replace up to 278 million jobs by 2049, representing 35.8% of the current workforce (Zhou et al., 2019).

The historical analysis of automation potential reveals varying predictions across different studies. A study by Frey and Osborne (2013) in the US showed that the rapid adoption of automation and new technologies will lead to radical changes in the labour market, as 47% of jobs could be automated by 2050. A study by Arntz et al. (2016) shows that on average, in 21 OECD countries, only 9% of jobs are fully automated. Manyika et al. (2017) suggest in their study that up to 30% of jobs could be automated by 2030 and more than 50% by 2050. Nedelkoska and Quintini (2018) estimate that in OECD countries, about 14% of jobs are at high risk of automation (i.e., probability of automation above 70%) and 32% of jobs are at significant risk (probability of automation between 50% and 70%). Smit et al. (2020) predict that in a medium scenario, 22% of current jobs could be automated by 2030. Meanwhile, Josten and Lordan (2020) make an even more radical prediction, suggesting that as many as 35

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percent of all jobs will be fully automated within the next decade. Lassébie and Quintini (2022) argue that, on average across OECD countries, about 28 percent of jobs are at high risk of automation. The authors stress that the increase in risk estimates compared to previous studies is due to the rapid advances in artificial intelligence technologies. The study reveals that 9% of workers are employed in occupations where at least 25% of skills are easily automated. This figure varies considerably between countries, from less than 6% to more than 30%. The percentage of people who are able to work with a high level of IT skills varies from less than 6% in the UK, Luxembourg, and Sweden to more than 12% in Hungary, Latvia, and Slovakia.

In this context, the sustainability of current tax systems is at stake. Labour taxation systems in advanced economies remain one of the main sources of tax revenue. According to the OECD (2024), the average labour tax wedge in the EU in 2023 was 41.56% (see Figure 1).

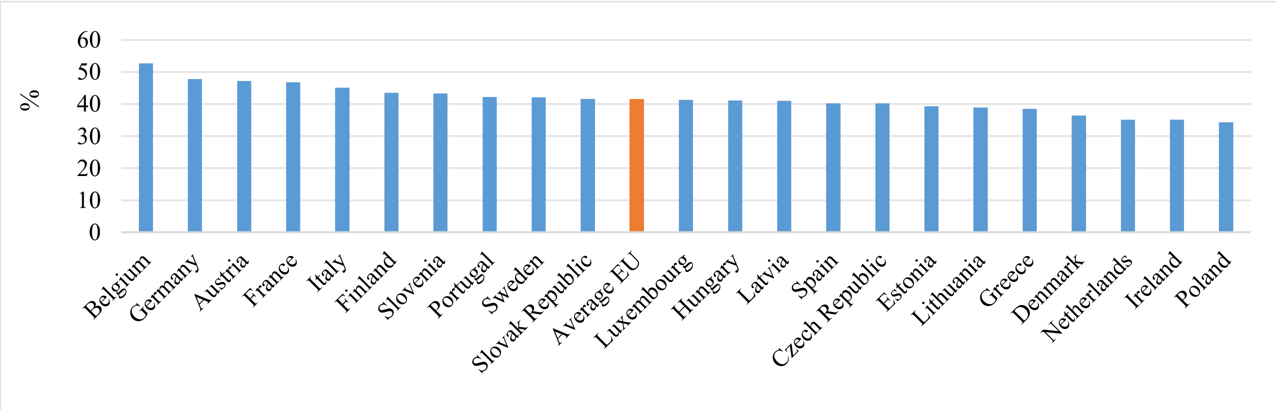

Figure 1. Tax Wedge in the EU[1], 2023. (OECD, 2024)

As the figure shows, there are significant differences between countries, ranging from 34.31% in Ireland to 52.73% in Belgium. Fischer et al. (2022) highlight that such a high labour tax burden has a negative impact on the EU's competitiveness in the global market, especially compared to the US and Asian countries.

Technological progress and its impact on employment can put public finances under two kinds of pressure: on the one hand, it will reduce tax revenues and, on the other, it will increase government expenditure. Prisecaru (2017) points out that technological developments reduce the demand for lower-educated and lower-skilled workers, which in turn increases structural unemployment. The OECD (2018) emphasises that if low-skilled or traditional workers are replaced by robots or work process automation without investment in retraining, unemployment and social inequalities will increase. These developments – structural unemployment, the increasing need for workforce retraining and educational reform funding, and the growth of socially vulnerable groups – present serious challenges to current tax systems.

In this context, reducing labour taxation could be an effective means of mitigating the negative impact of technological progress on employment whilst maintaining its positive effects. The issue of reducing labour taxation has been significant for decades and has been the subject of considerable research.

Pierrard (2004) examines labour tax reductions and finds that they help to slow job destruction and create more employment opportunities. Heijdra and Ligthar (2009) argue that a straightforward and practical reform of labour income taxes will increase employment, reduce unemployment and have a positive impact on government revenues.

Ziegenbein (2017), analysing the reduction of the labour income tax burden,

[1] *Excluding Bulgaria, Croatia, Cyprus, Malta, and Romania.*

argues that tax cuts can have a significant impact on the economy during periods of prosperity, whilst their impact may be minimal during periods of high unemployment and economic downturn. Jacquinot et al. (2018) assessed the impact of reducing labour tax rates in the euro area and found that domestic tax rate reductions would have a stimulative effect on the domestic economy and employment, whilst coordinated reductions in labour income taxes could lead to more significant increases in economic activity and employment across the euro area.

Rossi (2020) emphasises that the effectiveness of labour tax cuts should be reinforced by policies that promote innovation, technological progress and human capital development, as sustainable economic growth depends not only on labour costs but also on the broader economic environment. Bielecki and Stähler (2022) find that reducing the labour income tax burden generates positive macroeconomic effects and aggregate welfare gains, regardless of the introduction of alternatives such as consumption, wealth or other taxes. Wang (2023) argues that lower labour taxes would stimulate employment growth by encouraging firms to hire more workers, which can be particularly effective in creating a more stable economic environment.

Thus, lower labour taxation would contribute to lowering labour costs and help retain workers, which is particularly important for low-skilled workers. Whilst tax cuts may slow down automation in some areas (where companies choose to retain human labour), they do not slow down overall technological progress, allowing companies to continue to innovate and improve efficiency, which would stimulate job creation and economic growth. Therefore, this study aims to empirically assess the feasibility and employment implications of labour taxation reform in the context of technological transformation. The research employs a general equilibrium model, which allows for a comprehensive assessment of the impact of changes in the tax system on macroeconomic indicators, including employment.

Recent studies have sought to identify the optimal structure of the tax system in the context of technological progress, using various economic models. Prettner and Strulik (2019), studying the impact of taxes on automation and inequality in a general equilibrium model, found that more favourable taxation of low-skilled workers reduces the supply of high-skilled workers and hinders economic growth. Zhang (2019), using a factor-specific partial equilibrium model, revealed two main effects of automation on the labour market: a crowding-out effect, where robots replace unskilled labour, and a capital reallocation effect, which can affect the wages of all workers.

Other researchers have focused on the effectiveness of a robot tax as a potential policy instrument. Gasteiger and Prettner (2022), using an OLG model, found that whilst automation reduces wages and households' investment potential, a robot tax can slow down technological progress and reduce the income of future generations. Thuemmel (2022), using a model with an occupational choice option, concluded that the benefits of a robot tax are minimal and implementation faces significant administrative challenges.

Recent studies emphasise the importance of an integrated approach to tax system reform. Jacobs and Thuemmel (2023), in a general equilibrium model, demonstrated the need to combine income taxation with education policy. Zhu et al. (2022) suggested introducing new taxes on automated capital whilst increasing government spending. Heer et al. (2023), using a neoclassical growth model, revealed significant long-run relationships between taxation of factors of production and the use of automated capital, emphasising that tax system reform needs to consider the interaction between all factors of production.

Despite these studies, significant gaps remain in the field of labour taxation and technological progress. Most existing studies focus on individual aspects – either the tax impact or the consequences of automation – but lack an integrated view of the interaction between these factors. Similarly, many studies rely on static models or analyse only long-run equilibria, without assessing how different levels of automation affect the effectiveness of tax reforms. Our study contributes to the existing literature by providing an empirical rationale for the effectiveness of labour tax reform at different stages of technological progress.

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The methodology of this study is distinguished by several aspects: 1) an integrated assessment of technological progress and tax policy, which allows for the identification of the efficiency of labour taxation at different stages of automation; 2) a comprehensive assessment of the interaction between macroeconomic indicators, which reveals not only the direct effects of tax reform on employment but also the secondary effects through changes in consumption, output and capital growth; 3) a comparative analysis of two scenarios – tax cuts and tax increases – which provides an empirical basis for the optimal direction of tax policy in a context of technological progress. The model is calibrated for the EU economic area, which is particularly relevant for making recommendations in the context of the EU countries' ambition to reconcile technological progress with labour market stability and social welfare.

Methodology

In this section a general equilibrium model is presented, allowing for the assessment of labour tax reform's impact on employment and other macroeconomic indicators at different levels of automation in the economy. The model is calibrated for the European Union economic zone using 2023 statistical data and relevant parameters from academic literature. The modelling section describes the simulation process and details the scenarios used to analyse the effects of changes in labour taxation.

The Model

The model framework builds upon recent literature examining the economic impacts of automation, particularly drawing from the works of Lankisch (2017), Torres (2020), Casas and Torres (2020), Gasteiger and Prettner (2022), and Casas and Torres (2024). The model employs a general equilibrium approach where the economy is conceptualized as an interaction between three primary agents: households, firms, and government.

Government

The government collects tax revenues and redistributes them to households through lump-sum transfers. The government budget constraint in each period t is defined as:

$$G_t = T_t - TF_t = 0 \quad (1)$$

where G_t represents the government budget, T_t denotes tax revenues, and TF_t represents lump-sum transfers to households.

Tax revenues are derived solely from labour income taxation:

$$T_t = t_t^l W_t L_t \quad (2)$$

where t_t^l represents the labour income tax rate, W_t is the wages, and L_t denotes labour hours, representing employment.

The model assumes that the government maintains a passive fiscal policy stance in each period, acting primarily as a redistributive mechanism. This specification allows us to focus on the direct effects of tax policy changes on employment and other macroeconomic variables without the complexities of general fiscal policy. The lump-sum transfer mechanism ensures that any changes in tax revenues are directly transmitted to household income, creating a clear channel for analysing the effects of tax policy modifications on economic agents' behaviour and outcomes.

Households

The model employs a representative household approach, where the household makes optimal decisions regarding consumption, labour supply, and investment in both traditional and automated capital. Crucially for our research focus, households are subject to labour income taxation[2].

The representative household maximises a logarithmic utility function that captures the trade-off between consumption and leisure:

$$U(C_t, 1 - L_t) = \gamma log C_t + (1 - \gamma) log(1 - L_t) \quad (3)$$

[2] *Below we present a condensed version of the key household sector equations to demonstrate how our research question is incorporated into the model. The complete mathematical framework and detailed derivations can be found in Casas and Torres (2020) and Casas and Torres (2024).*

where C_t represents consumption, L_t represents labour, and γ is a preference parameter reflecting the relative weight of consumption in the household's utility function.

The primary constraint faced by households is their budget constraint. Households have limited income and must allocate their resources between consumption and savings. The household budget constraint is expressed as:

$$C_t + S_t = (1 - t_t^l)W_t L_t + R_{k,t}K_t + R_{d,t}D_t + TF_t \tag{4}$$

where S_t represents savings, K_t is traditional capital, D_t is automated capital, and R_t – are the respective rates of return on capital.

To reduce model complexity, we assume that $S_t = I_t$, meaning savings (S_t) are converted to investments (I_t) without incurring any investment risk, transaction costs, or administrative fees (Torres, 2020).

Investments encompass both traditional and automated capital:

$$I_t = D_{t+1} - (1 - \delta_d)D_t + K_{t+1} - (1 - \delta_k)K_t \tag{5}$$

where I_t represents total investments δ_k and δ_d are the respective depreciation rates for each type of capital.

Solving the household's maximization problem yields the following first-order conditions (FOC):

$$C_t = \frac{\gamma}{1-\gamma}(1 - L_t)W_t(1 - \tau_t^l) \tag{6}$$

$$1 = \beta\frac{C_t}{C_{t+1}}\left(\left(R_{k,t+1} - \delta_k\right) + 1\right) \tag{7}$$

$$1 = \beta\frac{C_t}{C_{t+1}}\left(\left(R_{d,t+1} - \delta_d\right) + 1\right) \tag{8}$$

These equations characterize the household's optimal choices regarding the trade-offs between consumption, investment, and leisure. Equation (6) represents the optimal labour-leisure choice, while equations (7) and (8) describe the optimal intertemporal allocation of consumption and investment in both types of capital.

Firms

In constructing the firm behavior equations within our research context, it is crucial to incorporate both traditional and automated capital into the production function[3]. We specify a CES production function that includes two types of capital – traditional capital and automated capital:

$$Y_t = K_t^a[\mu D_t^v + (1 - \mu)L_t^v]^{\frac{1-a}{v}} \tag{9}$$

where Y is output, μ is a distribution parameter determining the share of automated jobs in the production process, and v is the substitution parameter between labour force and automated capital.

Technological progress in this production function is captured by the parameter μ, which determines the share of automated jobs in the production process. Automated jobs and human labour can coexist only when the automated jobs share parameter falls within the interval $0 < \mu < 1$. When $\mu = 0$, there are no automated jobs, while $\mu = 1$ implies full automation with no human labour input.

Firms maximise profit by choosing the optimal combination of labour force, traditional capital, and automated capital:

$$\max\Pi_t = Y_t - W_t L_t - R_{k,t}K_t - R_{d,t}D_t \tag{10}$$

From the first-order conditions (FOC) of the profit maximization problem, the marginal product of each factor is determined as:

$$W_t = \frac{1-\alpha}{v}K_t^\alpha[\mu D_t^v + (1-\mu)L_t^v]^{\frac{1-\alpha}{v}-1}[(1 - \mu)vL_t^{v-1}] \tag{11}$$

$$R_{k,t} = \alpha K_t^{\alpha-1}[\mu D_t^v + (1-\mu)L_t^v]^{\frac{1-\alpha}{v}} \tag{12}$$

$$R_{d,t} = \frac{1-\alpha}{v}K_t^\alpha[\mu D_t^v + (1 - \mu)L_t^v]^{\frac{1-\alpha}{v}-1}[v\mu D_t^{v-1}] \tag{13}$$

Under the assumptions of perfect competition and constant returns to scale, total output is fully distributed among production factors – labour force, traditional capital, and automated capital – yielding zero economic profits in equilibrium. This specification allows us to track how changes in labour taxation affect factor income distribution in an automating economy. The framework is particularly suitable for analysing how tax policy can address the labour market challenges posed by increasing automation.

[3] *We present here a simplified version of the key equations, focusing on aspects relevant to our research question. The complete specification and detailed derivations can be found in Lankisch (2017) and Gasteiger and Prettner (2022).*

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Calibration

The model is calibrated to the statistical data and to the values used in the relevant empirical literature. The calibration is done in such a way that the model is as close as possible to the 2023 EU data. The values of the model parameters are given in the table below (see Table 1).

Table 1. Model Parameters for 2023

Notation	Parameter	Value	Source
t_t^l	Labour income tax rate	41.56%	OECD (2024)
μ	Share of automated jobs in the production process parameter	[0,1; 0,5]	Frey and Osborne (2013), Arntz et al. (2016), Manyika et al. (2017), Nedelkoska and Quintini (2018), Smit et al. (2020), Josten and Lordan (2020), Lassébie and Quintini (2022)
υ	Labour and automated capital substitution parameter	0,33	Furusawa et al., 2022
$\delta_{k,t}$	Traditional capital depreciation rate	0,09	Based on EU KLEMS
$\delta_{d,t}$	Automated capital depreciation rate	0,25	Based on EU KLEMS
α	Capital share	0,3	Bozou and Creel (2023)
β	Discount factor	0,99	Rubio and Comunale, 2017
γ	Consumption and leisure choice parameter	0,4	Torres (2020), Casas and Torres (2020), Casas and Torres (2024)

**Source: compiled by authors.*

The model calibrates the *labour income tax rate* based on the tax wedge[4], which averages 41.56% across EU countries. The tax wedge measures the total tax burden on labour, including taxes and social security contributions paid by employees and employers, as a percentage of total labour income.

Another important parameter is *the share of automated jobs in the production process parameter (μ)*, which represents the proportion of the final product produced using fully automated jobs. In other words, it reflects the employment effects of technological progress in the model. Its value ranges from 0 to 1, where μ = 1 indicates fully automated production without human intervention, and μ = 0 reflects a traditional production process without automation. For the purposes of the study, the value of the parameter varies within the range [0.1; 0.5] (10%; 50%). A review of the literature[5] shows that the potential for automation, according to different studies, ranges from 9% (Arntz et al., 2016) to 50% (Frey and Osborne, 2013).

The labour and automated capital substitution parameter (υ) shows how easily automated capital can replace human labour in the production process. The value of this parameter determines the elasticity of substitution between labour and automated capital (σ), which is calculated according to the formula υ = (σ - 1) / σ (Acemoglu and Restrepo, 2017). The parameter value used in the study is υ = 0.33 (σ = 1.5). This value was chosen given the different elasticities of substitution between robots and low-skilled workers (σ = 1.923) and between artificial intelligence and high-skilled workers (σ = 0.91) (Furusawa et al., 2022).

Traditional ($\delta_{k,t}$) and automated capital ($\delta_{d,t}$) depreciation rates are chosen based on the depreciation rates used in the EU KLEMS for ICT assets and non-ICT assets (Timmer et al., 2007; Stehrer et al., 2019). ICT assets, which include computer hardware, software, and communication technologies, are consistent with the concept of automated capital, while non-ICT assets are more representative of traditional

[4] *Excluding Bulgaria, Croatia, Cyprus, Malta, and Romania.*

[5] *See Literature Review.*

capital (Jäger, 2017). The study uses average depreciation rates for each group: ICT assets are averaged for automated capital at 25%, while non-ICT assets are averaged for traditional capital at 9%.

Capital share parameter (α) for growth in advanced economies, the value of this parameter ranges from 0.25 to 0.35 (Torres, 2020, Cardani et al., 2022). The parameter is chosen according to Bozou and Creel (2023) for a value of 0.3 for the Eurozone. *The discount factor (β)* from Kydland and Prescott (1982) in the literature on DSGE models is taken as the standard value for this parameter of 0.99 (Rubio and Comunale, 2017). The value chosen for the *consumption-leisure preference parameter (γ)* is 0.4, based on the studies of Casas and Torres (2020) and Casas and Torres (2024).

The modelling

The modelling analysis aims to assess the effects of labour income taxation changes on employment and other macroeconomic indicators in the context of technological progress. The study examines two alternative scenarios: a decrease and an increase in the labour income tax rate. The results of these scenarios are compared with a baseline model that applies the average labour income tax rate.

In the scenarios, new labour income tax rates were selected based on the EU Tax Wedge statistical analysis (see Table 2).

Table 2. Statistical Analysis of Labour Income Tax rates in the EU, 2023

Statistical measure	Rate (%)
Minimum value (Q0)	34.31
First quartile (Q1, 25th percentile)	39.02
Median (Q2, 50th percentile)	41.24
Third quartile (Q3, 75th percentile)	43.49
Maximum value (Q4)	52.73
Overall average	41.56

**Source: OECD (2024).*

The baseline model applies the average labour income tax rate (41.56%), which falls between the second and third quartiles. To avoid drastic changes, the tax reduction scenario uses the first quartile (Q1) rate of 39.02%, whilst the tax increase scenario employs the third quartile (Q3) rate of 43.49%.

The main macroeconomic indicators selected for the assessment of the simulation results are employment, production, consumption, tax revenue, investment, and traditional and automated capital. The assessment is carried out by analysing changes in these indicators as the economy moves from one steady state to another, taking into account different levels of technological progress. Technological progress in the model is expressed in terms of the share of automated jobs (μ), which reflects the proportion of automated jobs in production. When tax rates are changed, economic agents react to these changes, and the resulting trajectories show how the economy adapts to the new conditions and moves from one steady state to another as the level of automation changes.

The research follows the methodology developed by Casas and Torres (2020) and Casas and Torres (2024). Calculations were performed using Python programming language. The model system is solved using the Levenberg-Marquardt algorithm, which is an efficient method for solving nonlinear systems, implemented through the SciPy optimisation library. The automated jobs parameter μ is analysed in the interval [0.1, 0.5], which is divided into 80 equal intervals. For each μ point, a steady state is calculated using convergence criteria: tolerance of 1e-6 and maximum of 1000 iterations. The results are visualised using the Matplotlib library, creating comparative curves for different scenarios.

There are methodological limitations to the application of the model. Firstly, the model only analyses steady states, without taking into account transient dynamics. Second, it does not take into account possible economic shocks and unexpected changes. Third, it makes standard assumptions about rational economic agents and perfect information. Despite these limitations, the model allows us to assess the long-run

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consequences of tax policy changes at different levels of automation.

Results

In this section, the simulation results and their analysis are presented. First, the impact of technological progress on employment and other macroeconomic indicators in the baseline model is assessed. Then, two alternative scenarios are analysed: a labour tax reduction scenario (from 41.56% to 39.02%) and a labour tax increase scenario (from 41.56% to 43.49%), comparing their effects with the baseline model.

Assessing the impact of technological progress on employment and other macroeconomic indicators in the baseline model

In examining the modelling results of the scenarios for changing labour income taxes, it is appropriate to first assess the impact of technological progress on employment and other macroeconomic indicators in the baseline model. This assessment will provide a basis for further analysis and establish benchmarks against which the results of the envisaged scenarios will be assessed.

The figure below shows the evolution of the main macroeconomic indicators – employment (L), production (Y), and consumption (C) – as the share of automated jobs increases. In other words, this figure shows how these indicators change as the share of automated jobs in the production process increases (see Figure 3.1).

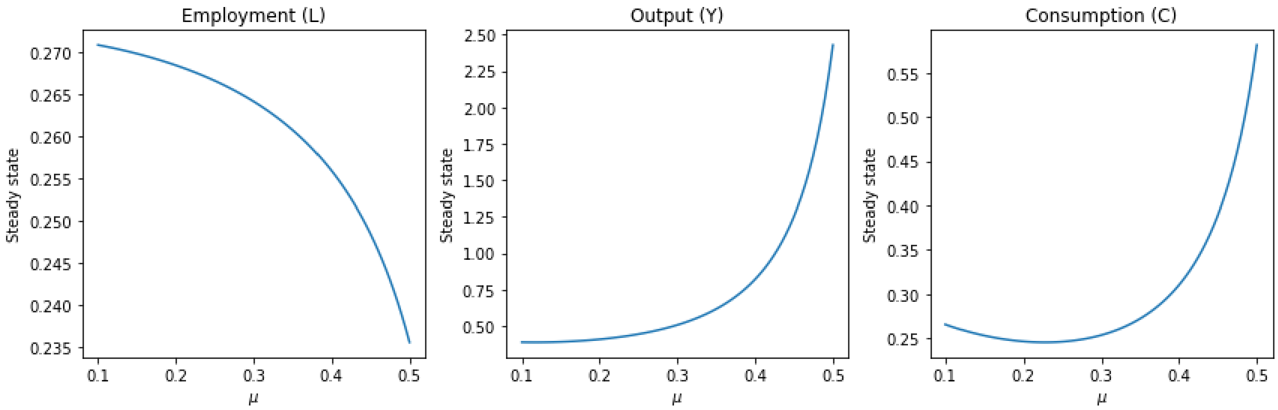

Figure 3.1. Dynamics of employment and other key macroeconomic indicators
(μ – share of automated jobs parameter)

Analysis of the data (see Figure 3.1) shows that as the share of automated jobs (parameter μ) increases, employment (L) initially decreases very slightly. However, once a certain threshold (μ~0.2) is reached, the decrease becomes more pronounced. This trend indicates that as automation gains momentum, labour demand decreases more rapidly. This reflects structural changes in the labour market, where the number of traditional jobs is declining due to the expansion of automation. Meanwhile, output (Y) is growing steadily and eventually increases several times its initial level. The increase is particularly pronounced when the level of automation reaches higher values (μ > 0.4). This confirms that higher levels of automation lead to significantly higher productivity. Although employment decreases, production efficiency and volumes increase as a result of automation, indicating positive changes in the production process. Consumption (C) also grows with increasing levels of automation, but at a slower rate compared to overall output growth. However, the consumption curve shows a less steep rise than the production curve, especially at higher levels of automation. This may be due to the fact that automation, while increasing the productivity of the economy, reduces the share of labour income in the overall income structure, which limits the growth of consumption. This divergence between fast-growing production and slower-growing consumption may be a sign of widening income inequality.

When analysing other macroeconomic indicators, such as investment (I) and traditional and automated capital (K and D), technological progress has a positive impact on growth (see Figure 3.2).

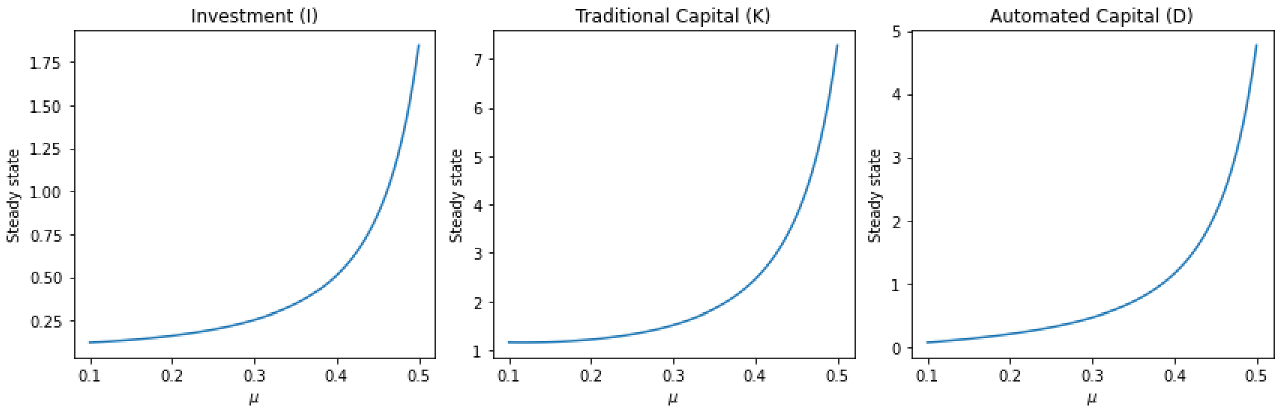

Figure 3.2. Dynamics of other macroeconomic indicators
(μ – share of automated jobs parameter)

The investment (I) curve shows a rapid increase (see Figure 3.2), especially when the level of automation reaches higher values, reflecting an increasing willingness to invest in expansion and production. The growth of traditional capital (K) is also significant, indicating that despite automation, the need for conventional capital goods and infrastructure remains. The growth curve for automated capital (D) is steepest, confirming that as the level of automation increases, high-tech capital grows significantly.

These results show that while automation has a positive impact on economic growth, it also poses significant challenges for employment and the distribution of income, especially labour. The economy is undergoing a structural change where the role of traditional work is declining but overall economic activity is growing. The consequence of these changes is increasing social inequality, which results from the declining share of labour income in the overall income structure.

The decline in the share of labour income in the total income structure is illustrated by the change in the share of total inputs in total production, with an increase in the share of automated jobs (μ) (see Figure 3.3).

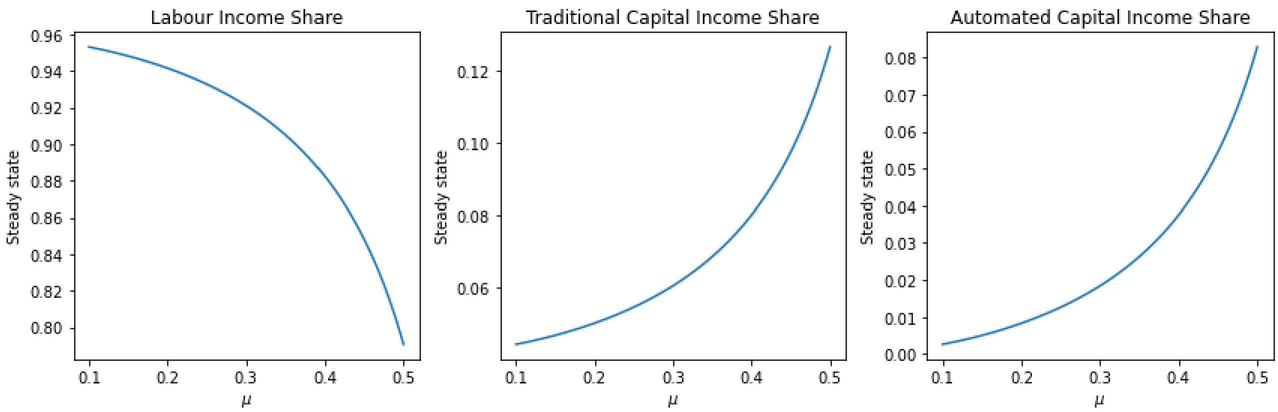

Figure 3.3. Changes in the share of labour, capital and automated capital income in the total income structure
(μ – share of automated jobs parameter)

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Figure 3.3 shows that as the value of μ increases, the importance of production resources and the distribution of income between them changes. The share of labour income in total income decreases significantly, while the share of automated capital income increases significantly. The share of capital income also increases slightly, but this change is smaller than for automated capital. These results show that automation reduces the importance of labour in production and increases the role of automated capital, which in turn changes the structure of total income.

These changes in the structure of income can have a significant impact on the government budget. As different productive resources (labour, traditional capital, automated capital) are taxed in different ways and at different rates, changes in the structure of income can affect tax revenues. In order to assess this impact, the following section examines the evolution of labour income tax collections in the light of technological progress.

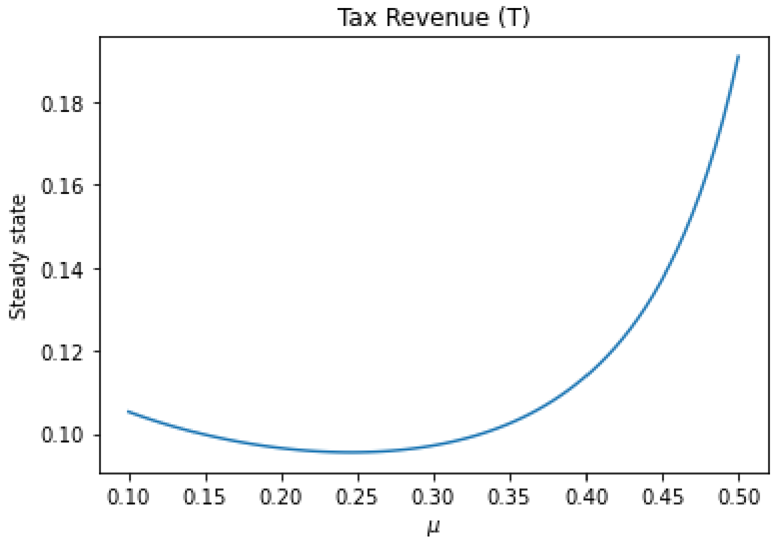

Figure 3.4. Tax revenue dynamics
(μ – share of automated jobs parameter)

Looking at the increase in tax revenue from labour income taxes in different periods (see Figure 3.4), it can be observed that in the short run, i.e., at lower values of the distribution parameter μ, tax revenue collection decreases, as it takes time for the economy to adjust. As the value of μ increases, tax revenue growth accelerates as technological progress becomes more pervasive in different areas of the economy, increasing productivity and the tax base. At the highest value of μ in the analysis, the increase in tax revenue is most pronounced as technological progress becomes an integral part of the economy and its positive impact on tax revenue reaches its peak.

However, although labour income tax collections are rising, this is not due to employment growth but to the increase in the labour income of the remaining labour market participants (see Figure 3.5).

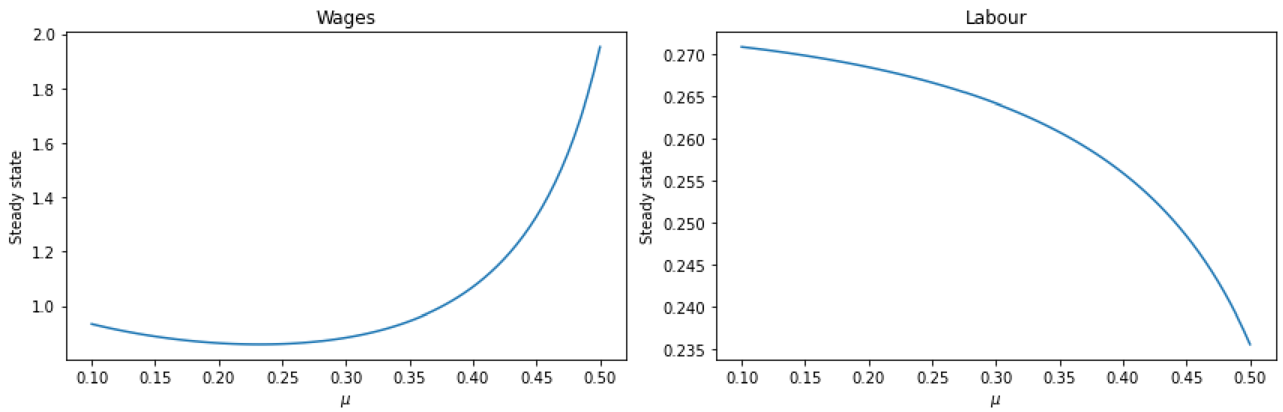

Figure 3.5. Wages and employment dynamics
(μ – share of automated jobs parameter)

This phenomenon, where labour income rises rapidly while employment falls, can significantly increase income inequality, increase the risk of the emergence of socially vulnerable groups, and raise social tensions in society. Although the model does not address these aspects directly, it can be assumed that the less-skilled workers, as well as some of the middle-skilled workers, are the most affected in this situation. As the demand for labour decreases due to technological progress, less-skilled workers face the risk of unemployment as their skills become less marketable. Middle-skilled workers may also be under pressure as some of their jobs may be automated. Meanwhile, highly skilled workers whose skills complement technology will enjoy higher growth in labour income.

This situation raises the risk of high structural unemployment, as some workers may no longer have marketable skills in a changing labour market. To mitigate these negative effects, it is important to invest in education, training, and retraining to enable workers to adapt to the changing needs of the labour market. It may also be important to introduce social protection measures to reduce income inequalities caused by technological progress and ensure social stability.

Thus, on the one hand, rising wages and overall economic growth can lead to higher tax revenues for the government budget. However, if income inequality increases and part of the population is exposed to a higher risk of unemployment, the government may need to increase its spending on social benefits and support programmes to mitigate the negative effects.

In summary, while technological progress can boost economic growth, its impact on the labour market and income distribution can pose challenges to government budgets and the financing of public services. In order to ensure sustainable economic growth and public welfare, it is important to find ways to adapt tax systems to changing conditions, for example, by reducing labour taxation to maintain employment levels.

Analysis of labour income tax change scenarios and their impact on macroeconomic indicators

Once the changes in the macroeconomic indicators in the baseline model have been identified, a further scenario (A) of a tax cut from 41.56% to 39.02% will be considered. A reduction in labour taxation in the context of technological progress should have a positive impact on employment levels for several reasons. Firstly, a reduction in the tax burden on labour would encourage employers to retain existing jobs and create new ones in line with the reduction in labour costs. In addition, lower labour costs may slow down the pace of job automation, giving more time for the labour market and workers to adapt to technological change.

Reducing labour taxation can also have a positive impact on the wider economy. Reducing the tax burden on labour income increases households' disposable income, which boosts consumption and economic growth. As a control, an alternative scenario is also considered, namely the scenario (B) of labour tax increases. In this scenario, labour income taxation is increased from 41.56% to 43.49%.

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However, it should be noted that a reduction in labour income taxation will inevitably have an impact on tax revenues. A reduction in the amount of taxes collected may lead to a budget deficit or the need to reduce public services.

The simulation results for the scenario (A) of a reduction in labour taxation are presented below. Simulation results for the two scenarios for the main macroeconomic indicators – employment (L), production (Y), and consumption (C) – taking into account the parameter μ (the share of automated jobs) are shown in Figure 3.6 The results obtained are compared with a baseline model (BS) in which no taxes are changed.

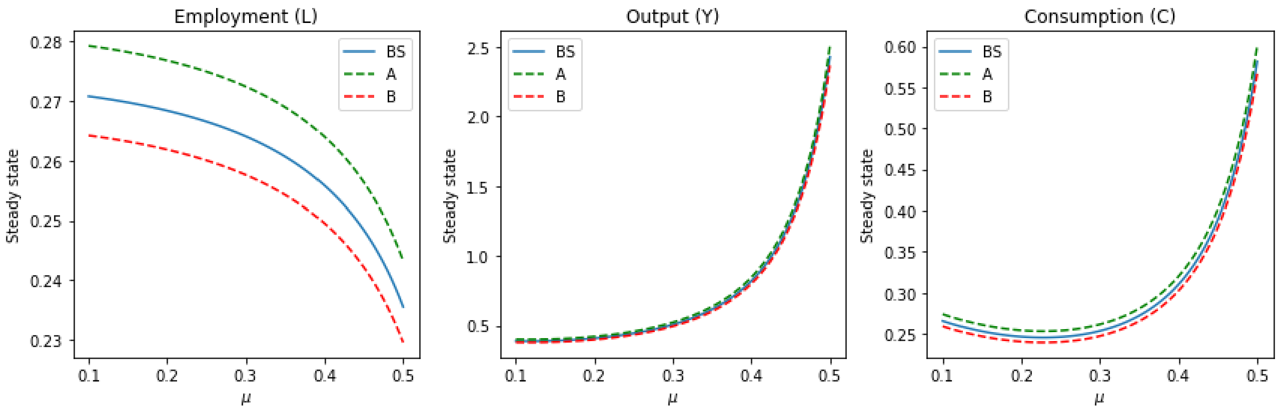

Figure 3.6. Dynamics of main macroeconomic indicators
(BS – baseline model, A – labour income tax reduction scenario, B – labour income tax increase scenario, μ – share of automated jobs parameter)

Comparing the labour income tax reduction scenario (A) with the baseline model (BS) (see Figure 3.6), employment (L) in scenario A is higher than in the baseline model, especially at lower levels of automation. This suggests that the reduction in labour income tax encourages firms to hire more workers due to lower labour costs. However, as the level of automation (μ) increases, the difference between Scenario A and the baseline model decreases slightly. This implies that the positive employment effect of a labour tax cut weakens under conditions of high automation, as firms still find it more attractive to invest in technology than in labour.

Output (Y) and consumption (C) are higher in Scenario A compared to the baseline across the whole range of values of μ. This suggests that a reduction in labour income tax increases production and consumption, as it raises the disposable income of the employed, which in turn leads to higher aggregate demand and higher investment in the expansion of production.

When analysing the results of the simulation of alternative scenario B, it can be observed that the increase in labour income taxes had a negative impact on a number of economic indicators compared to the baseline model (BS). Output (Y) in scenario B is lower than in scenarios BS and A, suggesting that higher labour taxes dampen economic activity. Employment (L) also declined, confirming that higher labour taxes reduce firms' incentives to hire. Consumption (C) is lower in scenario B, as households are left with less disposable income as a result of higher taxes.

Changes in labour income taxes also affect other macroeconomic indicators (see Figure 3.7).

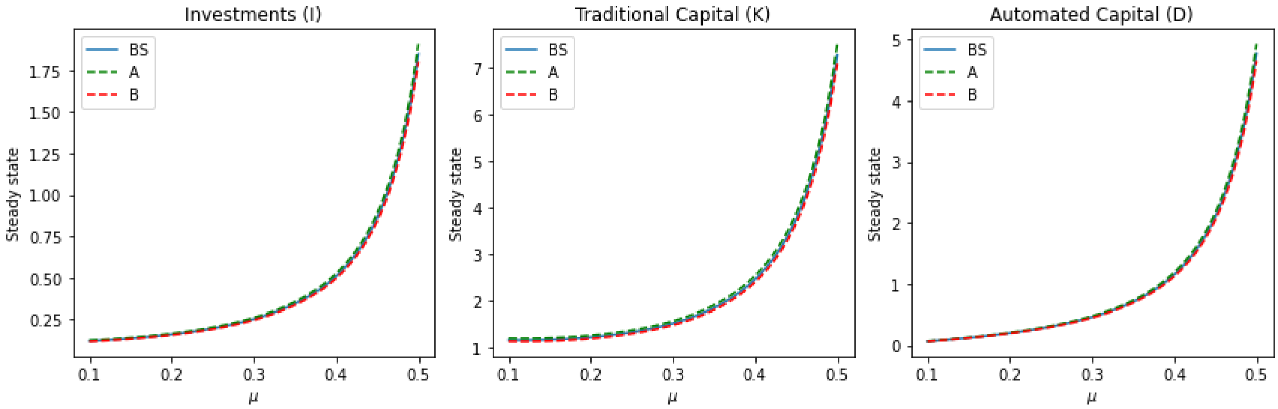

Figure 3.7. Dynamics of other macroeconomic indicators
(BS – baseline model, A – labour income tax reduction scenario, B – labour income tax increase scenario, μ – share of automated jobs parameter)

Investment (I) in Scenario A is higher than in the baseline model (see Figure 3.7), and this difference increases with the level of automation. This confirms that lower labour taxes and higher economic activity boost investment. Capital (K) grows faster in Scenario A than in the BS scenario, suggesting that lower labour taxes and higher economic activity encourage capital formation. Automated capital (D) is slightly higher in Scenario A than in the BS scenario at low levels of automation, but the difference is very small. This suggests that lower labour income taxes slightly reduce the incentive to automate, especially at low levels of automation. However, at higher levels of automation, the difference between A and BS becomes more pronounced, showing that in the long run, automation remains more attractive than traditional work.

When analysing scenario B, it is noticeable that all the indicators are lower than in the case of BS and A. These results show that economic growth, expansion, and the willingness to invest in development are being held back. It is important to note that the negative impact of scenario B on the economy is amplified as the level of automation increases. This suggests that high taxes on labour income can be particularly harmful in an economy with rapid automation, as they can further accelerate the substitution of technology for labour and increase inequality.

On balance, Scenario A is more favourable than Scenario B. However, the issue of tax revenue collection (T) remains (see Figure 3.8).

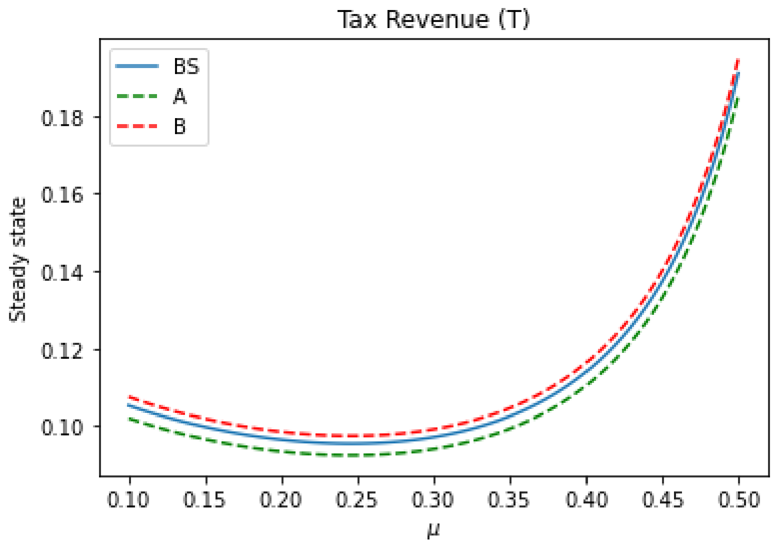

Figure 3.8. Tax revenue dynamics
(BS – baseline model, A – labour income tax reduction scenario, B – labour income tax increase scenario, μ – share of automated jobs parameter)

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Tax revenue (T) is lower in Scenario A than in the baseline model, as the reduction in labour income tax directly reduces the amount of taxes collected. While the increase in economic activity and consumption partly compensates for the loss of tax revenue, it is not sufficient to fully cover the fall in labour taxes. However, at high levels of automation, the tax revenue gap between the analysed scenarios narrows. This may be due to the fact that a higher level of automation leads to higher production efficiency and overall economic growth, which in turn generates higher tax revenues from other sources.

In scenario B, only the collection of tax revenue (T) increases due to higher taxation. However, this positive effect diminishes as the level of job automation (μ) increases, as higher labour taxes encourage firms to switch to automation more quickly, thus reducing the tax base for labour income.

In summary, reducing labour income tax rates as an option for reforming the tax system can have a positive impact on the economy, especially at relatively low levels of manufacturing automation. Scenario A shows increases in employment, output, consumption and other indicators compared to the baseline (BS). While labour income tax collections fall, the increase in economic activity leads to higher collections of consumption and capital income taxes, partly compensating for the loss of tax revenues.

However, in the longer term, as technological progress accelerates, the effectiveness of labour income tax cuts diminishes, as it remains more attractive for firms to invest in automation rather than in labour. Therefore, additional measures to reform the tax system, such as increasing taxes on consumption or capital income, may be necessary to balance public finances and ensure sustainable economic growth.

Conclusions

The study reveals a complex relationship between labour taxation and the impact of technological progress on employment. Using a general equilibrium model calibrated for the EU economy, it found that a reduction in labour income taxes from 41.56% to 39.02% has a positive, but declining effect on employment over time. The simulation results show that the effectiveness of tax cuts depends on the level of automation: at lower levels of automation ($\mu < 0.2$), tax cuts significantly increase employment, but this effect weakens as automation increases. The study also reveals that while tax cuts stimulate economic activity, production and consumption, they put significant pressure on public finances through reduced tax revenues.

The simulation results showed that tax cuts on labour income have a broader positive impact on the economy than just increasing employment. There are significant positive effects on investment, aggregate output and consumption. These findings are further strengthened by a control study which simulated an increase in labour income taxes from 41.56% to 43.49%. This scenario showed exactly the opposite results: a decrease in employment, production, consumption and investment, which empirically confirms the superiority of a policy of reducing labour taxes in the context of technological transformation.

The analysis suggests that reducing labour taxation may be an effective but insufficient tool to address the challenges posed by technological progress to the labour market. On the one hand, lower labour taxes increase firms' incentives to retain employees and create new jobs, which is particularly important during the transition period when the economy is adapting to technological change. On the other hand, the simulation results show that in the long run, even significant reductions in labour taxes cannot halt the structural decline in employment as the level of automation increases. In addition, reduced tax revenue collection limits the government's ability to finance the necessary retraining programmes and social security systems.

The results of the study justify the need for a comprehensive reform of the tax system, which would include not only a reduction in labour taxation but also the development of other sources of tax revenue. Future research should focus on modelling alternative scenarios for tax increases (e.g. on consumption or capital) in order to identify the optimal mix of taxes to maintain the sustainability of public finances without undermining economic competitiveness. It is also important to explore in more depth the sensitivity of different skill groups to tax changes and to analyse how the tax system can contribute more effectively to the adaptation of the workforce to technological change.

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