Optimal Taxation of Automation

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Abstract

This paper develops a general equilibrium model that distinguishes between low-skill and high-skill automation and integrates these distinctions into a quantitative optimal taxation framework. Modeling both types of automation is crucial because each has a distinct impact on wage dynamics across different skill groups. Specifically, low-skill automation exerts downward pressure on low-skill wages, thereby increasing wage inequality, whereas high-skill automation tends to reduce high-skill wages, thus mitigating wage disparities. The results indicate that distorting automation adoption can be an effective policy tool for influencing relative wages and achieving redistributive goals. In particular, the optimal policy involves taxing low-skill automation while subsidizing high-skill automation to compress wage inequality. The model is calibrated to the U.S. economy using multiple dimensions, and the government determines the optimal mix of automation taxes to maximize a Utilitarian social welfare function, accounting for transitional dynamics. The optimal policy combination is found to be a 23% tax on low-skill automation and a 1% subsidy on high-skill automation, leading to a redistribution of income from high-skill to low-skill workers. Taxing low-skill automation reduces the range of tasks where automation is more cost-effective than low-skill labor, thereby exerting upward pressure on low-skill wages. Conversely, subsidizing high-skill automation lowers high-skill wages. As a result, wage inequality declines from an initial value of 1.9 to 1.8 during the transition, and both pre- and post-tax income inequality decrease. Additionally, the labor share of income rises by 1 percentage point relative to the status quo. However, the optimal tax policy distorts capital accumulation, leading to a significant decline in aggregate capital and output over the transition period. These findings highlight the trade-offs involved in using automation taxes for redistributive purposes.

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1 Introduction

The rise in automation technologies is at the forefront of discussions regarding the demand for labor and the future of work. Over the past few decades, the US economy has undergone significant changes in the task content of production due to rapid advancements in automation technologies (Acemoglu and Restrepo (2019)).[1] A vast economic literature suggests that automation is a strong candidate to explain the observed decline in share of labor in national income, increase in wage inequality, and decline in wage growth since late 1980s.[2]

The scope of these advances are not limited to the rise of industrial robots and other automated machinery that displaces workers from routine and manual tasks. Recent advances in artificial intelligence and machine learning lead to automation of some complex tasks that require judgment, problem solving and analytical skills.[3] This implies that automation replaces both skilled and unskilled labor. The advances in automation technologies are beneficial as adoption of those technologies brings productivity gains. However, since these gains are not evenly distributed across agents, there are significant distributional consequences. The literature suggests that automation is a strong candidate to explain the observed decline in share of labor in national income, increase in wage inequality, and decline in wage growth since late 1980s[4]. For instance, Acemoglu and Restrepo (2020) estimates that one more industrial robot per thousand workers reduces aggregate wages by about 0.42%. Their estimates suggest that 85% of workers with less than a college degree and 15% of those with a college degree or more are negatively affected by adoption of industrial robots in terms of wages. They estimate negative and significant effects of industrial robots below the 85th percentile of the wage distribution for workers with less than a college degree, whereas the negative effects concentrate below the 15th percentile for those with a college degree or more.

Automation generates asymmetric effects across groups, and as a result inequality deepens. Thus there is a role for tax policy to deal with negative implications of automation. The goal of this paper is to answer the following question. Given the distributional consequences of automation, how should tax policy respond? In order to do so, the paper provides a general equilibrium model that distinguishes between low-and high-skill automation. We find that it is optimal to distort automation adoption in order to affect relative wages to provide redistribution. In particular, it is optimal to tax low-skill automation while subsidize high-skill automation to compress wage inequality. As in Acemoglu and Restrepo (2018a), low-skill (high-skill) automation corresponds to the automation of tasks that previously performed by low-skill (high-skill) labor. The term automation refers to the replacement of labor by capital that includes industrial robots, machines, specialized software and algorithms. To the best of our knowledge, this paper is the first one in the literature that incorporates low- and high-skill automation into a quantitative optimal taxation framework. Modeling the two types of automation is

[1] The task content of production refers to the allocation of tasks to the factors of production; mainly how tasks are allocated to capital and labor.

[2] See Autor et al. (2003), Autor et al. (2008), Acemoglu and Restrepo (2019), Acemoglu and Restrepo (2018c), Acemoglu and Restrepo (2020), Acemoglu and Restrepo (2022) among many others.

[3] For instance, Chui et al. (2015) estimates that financial planners, physicians, and senior executives have a significant amount of activity that can be automated by adapting current technology.

[4] Autor et al. (2003); Autor et al. (2008); Acemoglu and Restrepo (2019) and several others.

important as both are empirically relevant and each has a different impact on wages of workers with different skill types. Low-skill automation increases wage inequality as it creates a downward pressure on low-skill wages, whereas high-skill automation tends to lower high-skill wages, hence it has the opposite effect on wage inequality. In the current version of the model, the skill types of workers are given and do not change over time.

We assume that the government is not allowed to use lump-sum transfers and skill-type specific income taxes to provide redistribution. Under these reasonable assumptions, both the Second Welfare Theorem and the production efficiency theorem of Diamond and Mirrlees (1971) do not hold as in the other papers on redistribution and optimal taxation of automation technologies (Costinot and Werning (2018); Thuemmel (2022); Guerreiro et al. (2021)). In the model, workers pay nonlinear labor income taxes to the government. In addition to that, the government imposes potentially different linear taxes on low-and high-skill automation that are paid by firms. Thus, there are two channels of redistribution, the first one comes from progressive labor income taxation. The latter comes from the automation taxes. As indicated above, low-and high-skill automation have different impacts on wage distribution. Thus, any combination of automation taxes affects relative wages.

To study optimal taxation, we first calibrate the model to the US economy along several dimensions. Since there is no quantitative paper that distinguishes between two types of automation technologies, this paper additionally contributes to the literature by providing a novel calibration strategy for such models. The calibration of productivity of capital relative to low-and high-skill workers is crucial to have a realistic level of overall automation and to match relative exposure to automation across skill groups. Accordingly, we calibrate the productivity of capital relative to low-skill workers to match share of labor in national income as in the data. This is an important data feature to match since automation directly affects labor share of income. Then, by using the estimates of Frey and Osborne (2017), we calibrate the productivity of capital relative to high-skill workers to match relative exposure to automation across low-and high-skill workers. Frey and Osborne (2017) estimates the probability of automation for 702 occupations. We divide those occupations into low-and high-skill categories according to required level of education using 0*NET data, and then for each category the average exposure to automation is computed using employment shares of the corresponding occupations as weights. In the calibrated economy, as supported in the data, low-skill workers are more vulnerable to automation, they earn less and have lower capital holdings relative to high-skill ones.

For a calibrated level of automation, we solve for the following tax reform. The government chooses the optimal combination of automation taxes to maximize a Utilitarian social welfare function by taking transition to the final steady state into account. The optimal combination is 23% tax on low-skill automation and 1% subsidy on high-skill automation, as a result there is a redistribution from high- to low-skill workers. This is because, tax on low-skill automation narrows the range of tasks in which the cost of automation is lower than that of low-skill workers, thus it creates an upward pressure on low-skill wages. While subsidy on high-skill automation has the opposite effect on high-skill wages. Over transition, wage inequality declines to 1.8 from the initially calibrated value 1.9. Consequently, consumption inequality and both before and after-tax income inequality decline. Moreover, labor share of income increases 1 pp. relative to status-quo. This is very important for redistributional purposes as capital income is much more unevenly distributed than labor income. However, optimal taxes distorts accumulation of capital, so aggregate capital and output drop significantly over transition. The welfare gains of the optimal combination are equivalent to increasing (decreasing) the consumption of low-skill (high-skill) workers by 1.99% (2.31%) at every period under the status-quo tax policy. However, the overall welfare increases by 0.44% as low-skill workers constitute the majority of the population.

2 Related Literature

In general, our paper is related to the extensive literature on optimal capital taxation, and in particular, it is related to emerging literature on redistribution and taxation of automation technologies that examines whether taxes on automation can mitigate its adverse distributional effects. However, to the best of our knowledge, no paper studies the design of optimal tax systems when automation technologies replace different skill types.

The recent and growing literature on taxation of automation technologies asks how taxes should respond to the automation of tasks previously performed by labor (Guerreiro et al. (2021); Thuemmel (2022); Costinot and Werning (2022)). In all of these papers, as in this paper, the production efficiency theorem of Diamond and Mirrlees (1971) fails because the set of available policy instruments is restricted.

Guerreiro et al. (2021) study a model of automation with routine and non-routine workers in which robots are substitutes for routine workers, but complements for non-routine ones in an overlapping generations framework. They solve for an optimal Mirrleesian tax system and find that it is optimal to tax robots while the current generations of routine workers, who can no longer move to non-routine occupations, are active in the labor force. The magnitude of the optimal tax rate on robots decreases as the population share of routine workers declines. Once these workers retire, optimal robot taxes are zero as then there are no distributional gains from taxing robots. Similarly, Thuemmel (2022) considers a model of automation with three types of workers: non-routine cognitive, non-routine manual, and routine - in which robots substitute for routine workers at medium incomes. Thuemmel (2022) finds that it is optimal to distort robot adoption to exploit general equilibrium effects for wage compression. In the model, wage compression reduces income-tax distortions of labor supply, which brings welfare gains. However, whether robots should be taxed or subsidized depends on their specific impact on wages. That is, both papers call for non-zero tax on robots to exploit its redistributional gains through wage compression similar to the rationale in this paper and in line with Naito (1999).

Costinot and Werning (2022) also study how tax policy should respond to adverse distributional implications of robot adoption in an environment where the production efficiency theorem of Diamond and Mirrlees (1971) does not hold due to incomplete set of available policy instruments.[5] They introduce optimal tax formulas on robots that are driven by the changes in the relative wage structure. Their analysis shows that while distributional motivations lead to imposing non-zero taxes on robots, the magnitude of these taxes tends to decrease as the automation process deepens.

[5] In general, they ask for how tax policy should respond to technological change either in the form of increasing robot adoption or expanded trade opportunities.

Relatedly, Acemoglu et al. (2020) shows that the U.S. tax system is biased against labor and favors capital. Hence, the tax system leads to excessive automation and suboptimally low levels of employment and labor share. They show that taxing excessive automation could be beneficial to correct the bias in the current tax system, where the objective is to raise employment, not provide redistribution. In contrast to this paper, in Acemoglu et al. (2020) the planner does not have any redistributional motivation instead the rationale behind taxing automation is to correct for the bias in the status quo tax system that generates excessive automation.

As automation refers to the replacement of labor by some specific types of capital, this paper is also related to the extensive literature on capital income taxation. This literature dates back to the seminal Chamley-Judd result that states capital should not be taxed in the long-run (Chamley (1986), Judd (1985)).[6] Within the literature on capital income taxation, our paper is mostly relevant to the papers that point out the implications of capital taxation in environments where capital has different degrees of complementarity with different skill types. Jones et al. (1997) study optimal linear taxation in a growth model with a representative household that includes two types of labor, skilled and unskilled, and show that under capital-skill complementarity (CSC) the optimal long-run capital tax rate may be positive if the labor income tax rate cannot be conditioned on skill type. Slavík and Yazici (2014) analyze the optimality of differential capital taxation under CSC. They solve for an optimal Mirrleesian tax schedule and find that it is optimal to tax equipment capital at a higher rate than structures.[7] Relatedly, Kina et al. (2023) study the role of CSC on optimal redistributive taxation in a rich quantitative environment. They find that the optimal capital income tax rate under CSC is significantly higher than the optimal tax rate in an identically calibrated model without CSC. In both papers, Slavík and Yazici (2014), Kina et al. (2023), the underlying mechanism is taxing capital, and hence, depressing its accumulation decreases the skill premium, providing indirect redistribution from the skilled to the unskilled agents that is similar to the mechanism behind this paper. However, it is important to distinguish the effects of automation vs. other types of technological progress-such as CSC and skill-biased technical change- on the wage structure to stress the distinct effects of the former. Automation displaces workers from tasks where they had comparative advantage, lowering their relative wage and even possibly their real wages. Technologies directly improving the productivity of skilled labor do not involve any displacement and always increase the wages of unskilled workers. Thus, evaluating the implications of capital taxation in the presence of automation is important to consider to design optimal fiscal policy.

3 The Model

We develop an infinite-horizon deterministic growth model featuring two distinct types of automation technologies: high-skill and low-skill. Automation technologies, in general, are defined as any technology that enables capital—such as robots, machines, or algorithms—to perform tasks previously al-

[6] See also the literature on capital taxation under incomplete markets setup, e.g. Aiyagari (1995), Domeij and Heathcote (2004), Conesa et al. (2009) among others.

[7] In their model CSC refers to the complementarity between equipment capital and skilled labor.

located to workers, which thus leads to the displacement of workers from these tasks (Acemoglu and Restrepo (2022)). Our framework differentiates between the two types of automation following the definitions by Acemoglu and Restrepo (2018a). Specifically, low-skill automation refers to the automation of tasks performed by low-skill workers (mainly the automation of routine and manual tasks). Conversely, high-skill automation refers to the automation of complex tasks performed by high-skill workers. Typically, automation generates two distinct effects on the demand for a replaced worker: a negative displacement effect and a positive productivity effect. The displacement effect occurs as automation narrows the set of tasks performed by workers, therefore lowering the demand for labor. On the other hand, automation increases productivity by substituting cheaper capital for labor, thus raising the demand for labor in non-automated tasks. Therefore, the equilibrium wage impact hinges on these opposing dynamics. Notably, automation consistently shifts the production to be more capital-intensive and hence reduces the labor share. We assume that there are two types of capital; one type of capital is denoted by M, which refers to dedicated machinery, specialized software, industrial robots, and algorithms that substitute labor at the micro level in the production process. The other type of capital, denoted by K, refers to capital structures that complement labor in the aggregate production.

3.1 Workers

There is a continuum of unit measure of workers who live infinitely. They are characterized by their exogenously given permanent skill levels, high-skill or low-skill.[8] The index j denotes skill types such that $j = h$ stands for high-skill workers, $j = l$ stands for low-skill workers. The fraction of high-skilled workers in the population is denoted by π_h, and the fraction of low-skilled is given by $\pi_l = 1 - \pi_h$. Workers have the same preferences over the unique consumption good and leisure; a worker of type j derives utility from consumption, c_j, and disutility from labor supply, l_j. They work in competitive labor markets, invest in two types of physical capital and rent their capital holdings to competitive firms; and pay non-linear labor income taxes to the government.

Given their initial capital holdings, type $j \in \{h, l\}$ workers solve the following problem to maximize their lifetime utility:

$$\max_{\{c_{j,t}, l_{j,t}, i^k_{j,t}, i^m_{j,t}\}_{t=0}^{\infty}} \quad \sum_{t=0}^{\infty} \beta^t U(c_{j,t}, l_{j,t}) \tag{1}$$

subject to

$$c_{j,t} + i^k_{j,t} + i^m_{j,t} = w_{j,t} l_{j,t} - T_t(w_{j,t} l_{j,t}) + r^m_t M_{j,t} + r^k_t K_{j,t} \tag{2}$$

$$K_{j,t+1} = (1 - \delta^k) K_{j,t} + i^k_{j,t} \tag{3}$$

$$M_{j,t+1} = (1 - \delta^m) M_{j,t} + q_t i^m_{j,t} \tag{4}$$

$$M_{j,0} > 0, \quad K_{j,0} > 0 \tag{5}$$

where $c_{j,t}$ denotes consumption, $l_{j,t}$ denotes labor supply, $w_{j,t}$ denotes type specific wage rate;

[8] Future directions include integrating the choice of skill acquisition into our model, enhancing our understanding of how automation and taxation affect equilibrium outcomes.

$K_{j,t}, M_{j,t}$ denote capital holdings, $i^k_{j,t+1}, i^m_{j,t+1}$ denote investments, r^k_t, r^k_t denote rental rates, δ^k, δ^m denote depreciation rate for non-automation and automation capital, respectively; $T_t(.)$ denotes labor income tax schedule at time t, q_t stands for the current state of the technology for producing automation capital[9], and β stands for the discount factor. We assume that $U(c,l)$ satisfies standard Inada conditions and derivatives are such that $U_c > 0$, $U_l < 0$, and $U_{cc}, U_{ll} < 0$.

In equilibrium, workers are indifferent between investing in automation or non-automation capital as they pay the same return. In other words, there is a no arbitrage condition for the two investment options such that:

$$R_t = r^k_t + 1 - \delta^k = q_{t-1}\Big(r^m_t + \frac{1-\delta^m}{q_t}\Big) \quad \forall t \tag{6}$$

where R_t is the gross return on savings at time t.

3.2 Production Side

We employ a task-based framework to model automation based on Moll et al. (2022), which builds on Zeira (1998), Acemoglu and Autor (2011), and Acemoglu and Restrepo (2018c).[10] This framework emphasizes the role of tasks—units of work activity—either performed by labor or automated by capital in the production process. It distinctly separates 'skills,' the capabilities workers possess for task completion, from 'tasks' themselves, as proposed by Acemoglu and Autor (2011). In this framework, skills facilitate task completion; they do not directly create output.

There are two intermediate good sectors in the economy, low-skill sector and high-skill sector. Each sector $z \in \{h, l\}$ produces output Y_z using type-z labor and/or capital M. The final good Y is produced using these sectoral outputs and capital K via a Cobb-Douglas production function:[11]

$$Y = Y_l^{\theta\omega} Y_h^{\theta(1-\omega)} K^{1-\theta} \tag{7}$$

where $0 < \omega < 1$ governs the importance of low-skill sector output Y_l in the final production, and $0 < \theta < 1$ controls the income share of capital K.

The sectoral output Y_z is produced by combining a unit continuum of tasks u with a Cobb-Douglas technology:

$$\ln Y_z = \int_0^1 \ln y_z(u) du, \quad z \in \{h, l\} \tag{8}$$

or equivalently, $Y_z = \exp\left[\int_0^1 \ln y_z(u)du\right]$ where $y_z(u)$ refers to the production level of task u.[12] Each

[9]Therefore, $1/q_t$ stands for the price of automation capital at time t. The forthcoming steps will involve modeling technical change, particularly focusing on the declining price of automation capital.

[10]Modeling automation using a task-based framework enables us to capture its effects on labor share. As Acemoglu and Restrepo (2018b) states, modeling automation simply as factor-augmenting technological change has a very limited power to capture the impact of automation on labor share.

[11]In this section, time subscripts are not used for convenience.

[12]The functional form in (8) is given by a specific case of a more general CES production function $Y_z = \Big(\int_0^1 y_z(u)^{\frac{\sigma-1}{\sigma}}\Big)^{\frac{\sigma}{\sigma-1}}$ where $\sigma \in (0,\infty)$ is the elasticity of substitution between tasks. When $\sigma = 1$, this functional form leads to (8) which simplifies the analysis.

task u can be produced using capital M and/or skill-z labor as follows:

$$y_z(u) = \psi_z(u)m_z(u) + l_z(u) \quad \forall\, u \in [0,1], \quad z \in \{h, l\} \tag{9}$$

where $l_z(u)$ is the quantity of labor z employed in task u, $m_z(u)$ is the quantity of capital in use to produce task u, and $\psi_z(u) \geq 0$ denotes the productivity of capital in task u of sector z. It is assumed that the function $\psi_z(u)$ is continuous and strictly decreasing over $[0,1]$, and the productivity of type-z labor is normalized to one for all tasks. Namely; labor z has a comparative advantage in higher-indexed tasks. As shown in equation (9), a fundamental characteristic of the task-based approach is the perfect substitutability of capital and labor at the task level.

The unit cost of producing task u using capital is $(1+\tau_z)\frac{r^m}{\psi_z(u)}$ where r^m is the rental rate on capital(machines) and τ_z is the linear tax rate on skill-z automation. The unit cost of producing task u using labor is w_z, that is, the wage rate of labor z. We assume that when indifferent between producing a task using capital or labor, firms produce with capital. This assumption, together with $\psi_z(u)$ being strictly decreasing, implies that there exists a threshold task α_z such that all tasks in $[0, \alpha_z]$ are produced using capital, and all tasks in $(\alpha_z, 1]$ are produced with labor z.

We assume that all tasks, sectoral outputs, and the final good are produced in a competitive environment. As in Moll et al. (2022), our assumptions include the mobility of capital between sectors, in contrast to labor which is immobile.

3.2.1 Sector z's problem

Let $p_z(u)$ be the price of task $y_z(u)$, and p_z be the price of sector z output Y_z. Given prices, sector z producers choose the type of input (labor or capital) to produce task u and choose the quantity of task u used in the production.

$$\max_{\{y_z(u),\ \alpha_z\}} \quad p_z Y_z - \int_0^{\alpha_z} p_z(u) y_z(u) du - \int_{\alpha_z}^1 p_z(u) y_z(u) du \tag{10}$$

where $\quad y_z(u) = \psi_z(u)m_z(u) \quad \forall\, u \in [0, \alpha_z], \quad y_z(u) = l_z(u) \quad \forall\, u \in (\alpha_z, 1]$

For the optimal level of automation, α_z, there are three possible cases:

1. If $\dfrac{(1+\tau_z)r^m}{\psi_z(u)} > w_z \quad \forall\, u \in [0,1]$, then $\alpha_z = 0$. That is, there is no type-z automation in equilibrium because it is always cheaper to produce with labor z instead of capital.
2. If $\dfrac{(1+\tau_z)r^m}{\psi_z(u)} < w_z \quad \forall\, u \in [0,1]$, then $\alpha_z = 1$. That is, full adoption of automation technologies is optimal in equilibrium, as it is always cheaper to produce with capital instead of labor z.
3. If there exists $u_z^* \in (0,1)$ such that
   - $\dfrac{(1+\tau_z)r^m}{\psi_z(u)} < w_z \quad$ for all $u \in [0, u_z^*)$

- $\dfrac{(1+\tau_z)r^m}{\psi_z(u_z^*)} = w_z$
- $\dfrac{(1+\tau_z)r^m}{\psi_z(u)} > w_z$ for all $u \in (u_z^*, 1]$,

then $\alpha_z = u_z^*$. That is, there is an interior level of type-z automation in equilibrium.

Throughout the paper, we focus on case 3; the equilibrium in which there is an interior level of automation in both sectors. The existence of interior automation is guaranteed by the following assumptions:

Assumption 1. *For all u, $\psi_z(u)$ is continuous and strictly decreasing in [0, 1].*

Assumption 2. *$\psi_z(0) \approx \infty$. That is, the cost of producing task $u = 0$ with capital is almost zero, hence it is never optimal to use labor z in task $u = 0$.*

Assumption 3. *$\psi_z(1) \approx 0$. That is, capital has very low productivity at task $u = 1$, hence it is never optimal to use capital in task $u = 1$.*

Under the assumptions (1)-(3), we could rewrite the problem of sector z producers as:

$$\max_{\{m_z(u), l_z(u), \alpha_z\}} \quad p_z Y_z - \int_0^{\alpha_z} \Big(\frac{(1+\tau_z)r^m}{\psi_z(u)}\Big)\psi_z(u) m_z(u) du - \int_{\alpha_z}^1 w_z l_z(u) du \tag{11}$$

where the optimality conditions read:

$$(1+\tau_z)\frac{r^m}{\psi_z(\alpha_z)} = w_z \tag{12}$$

$$m_z(u) = \frac{p_z Y_z}{(1+\tau_z)r^m} \quad \forall\, u \in [0, \alpha_z] \tag{13}$$

$$l_z(u) = \frac{p_z Y_z}{w_z} \quad \forall\, u \in (\alpha_z, 1] \tag{14}$$

Equation (13) implies that for tasks in $[0, \alpha_z]$, the quantity of capital required to produce $y_z(u)$ is $\frac{p_z Y_z}{(1+\tau_z)r^m}$. Therefore, the total amount of capital used in sector z is given by:

$$M_z = \frac{p_z Y_z}{(1+\tau_z)r^m}\alpha_z \tag{15}$$

Similarly, equation (14) implies that for tasks in $(\alpha_z, 1]$, the quantity of labor z required to produce $y_z(u)$ is $\frac{p_z Y_z}{w_z}$; and hence, the total amount of labor of type-z demanded in sector z is given by:

$$L_z = \frac{p_z Y_z}{w_z}(1 - \alpha_z) \tag{16}$$

It follows that the equilibrium output of sector z can be written as a Cobb-Douglas production function, with endogenous exponents governed by the equilibrium automation level in sector z:

$$Y_z = \exp\Big[\int_0^{\alpha_z} \ln \psi_z(u)du\Big]\Big(\frac{M_z}{\alpha_z}\Big)^{\alpha_z}\Big(\frac{L_z}{1-\alpha_z}\Big)^{1-\alpha_z}, \quad z \in \{h, l\} \tag{17}$$

Compared to the standard Cobb-Douglas, the difference here is that the income share parameters are endogenously determined as a result of the profit maximization problem. This captures the direct impact of automation on factor shares: apart from its effects on the wage structure, automation lowers the share of income that goes to the replaced workers.

3.2.2 Final Good Sector

The price of the final good is normalized to 1. The final good producers solve the following maximization problem; they choose the quantity of sector z output Y_z for $z \in \{h, l\}$ to buy, and the quantity of capital structures, K to rent:

$$\max_{K,\{Y_z\}_{z\in\{h,l\}}} Y_l^{\theta\omega} Y_h^{\theta(1-\omega)} K^{1-\theta} - \sum_z p_z Y_z - (1+\tau_k) r^k K \tag{18}$$

where r^k and τ_k are the rental rate and the linear tax rate on capital structures, respectively.

3.3 Government

In each period, the government levies constant linear taxes on both low-skill and high-skill automation, denoted as τ_l and τ_h, respectively. Additionally, it imposes non-linear taxes on labor income and linear taxes on capital structures, represented by τ_k. The taxation rates for low- and high-skill automation may vary, with a negative rate indicating a subsidy. However, the tax schedule for labor income remains uniform across different skill types. The government uses the total tax revenue to finance its exogenously given expenditures, $\{G_t\}_{t=0}^{\infty}$. This leads to the following budget constraint for the government:

$$G_t = \tau_l r_t^m M_{l,t} + \tau_h r_t^m M_{h,t} + \sum_{z\in\{h,l\}} \pi_z T_t(w_{z,t} L_{z,t}) + \tau_k K_t \tag{19}$$

where $T_t(.)$ stands for the non-linear labor income tax schedule at time t.

3.4 Competitive Equilibrium

Definition. *Given the fraction of low- and high-skill workers, and each skill type's initial capital holdings, a deterministic competitive equilibrium consists of a set of decision rules* $\{c_{j,t}, i^m_{j,t}, i^k_{j,t}, l_{j,t}\}_{j\in\{h,l\}}$ *for workers, a set of decision rules* $\{\{m_{z,t}(u)\}_{u=0}^{\alpha_{z,t}}, \{l_{z,t}(u)\}_{u=\alpha_{z,t}}^{1}, M_{z,t}, L_{z,t}, \alpha_{z,t}\}_{z\in\{h,l\}}$ *and* $\{\{Y_{z,t}\}_{z\in\{h,l\}}, K_t\}$ *for sector z producers and final good producers, respectively; a set of government policies* $\{\{\tau_z\}_{z\in\{h,l\}}, T_t(.), \tau_k\}$*, and prices* $\{\{p_{z,t}, w_{z,t}, \{p_{z,t}(u)\}_{u\in[0,1]}\}_{z\in\{h,l\}}, r_t^m, r_t^k, \frac{1}{q_t}\}$ *such that:*

1. *Given prices, initial capital holdings and government policies; the decision rules* $\{c_{j,t}, i^m_{j,t}, i^k_{j,t}, l_{j,t}\}_{j\in\{h,l\}}$ *solve type-j workers' utility maximization problem:*

$$\max_{\{c_{j,t}, l_{j,t}, i^k_{j,t}, i^m_{j,t}\}_{t=0}^{\infty}} \quad \sum_{t=0}^{\infty} \beta^t U(c_{j,t}, l_{j,t})$$

subject to

$$c_{j,t} + i^k_{j,t} + i^m_{j,t} = w_{j,t} l_{j,t} - T_t(w_{j,t} l_{j,t}) + r^m_t M_{j,t} + r^k_t K_{j,t}$$

$$K_{j,t+1} = (1-\delta^k) K_{j,t} + i^k_{j,t}, \quad M_{j,t+1} = (1-\delta^m) M_{j,t} + q_t i^m_{j,t}$$

$$M_{j,0} > 0, \;\; K_{j,0} > 0$$

2. *Given prices and government policies; the decision rules* $\{\{m_{z,t}(u)\}_{u=0}^{\alpha_{z,t}}, \{l_{z,t}(u)\}_{u=\alpha_z}^{1}, M_{z,t}, L_{z,t}, \alpha_{z,t}\}_{z \in \{h,l\}}$ *solve sector* z *producers' profit maximization problem:*

$$\max_{\{y_{z,t}(u), \;\; \alpha_{z,t}\}} \quad p_{z,t} Y_{z,t} - \int_0^{\alpha_{z,t}} p_{z,t}(u) y_{z,t}(u) du - \int_{\alpha_{z,t}}^{1} p_{z,t}(u) y_{z,t}(u) du$$

such that $\quad y_{z,t}(u) = \psi_z(u) m_{z,t}(u) \quad \forall\, u \in [0, \alpha_{z,t}], \quad y_{z,t}(u) = l_{z,t}(u) \quad \forall\, u \in (\alpha_{z,t}, 1]$

where the optimality conditions yield:

$$(1+\tau_z) \frac{r^m_t}{\psi_z(\alpha_{z,t})} = w_{z,t}$$

$$M_{z,t} = \int_0^{\alpha_{z,t}} m_{z,t}(u) du = \frac{p_{z,t} Y_{z,t}}{(1+\tau_z) r^m_t} \alpha_{z,t}$$

$$L_{z,t} = \int_{\alpha_{z,t}}^{1} l_{z,t}(u) du = \frac{p_{z,t} Y_{z,t}}{w_{z,t}} (1 - \alpha_{z,t})$$

3. *Given prices and government policies; the decision rules* $\{\{Y_{z,t}\}_{z \in \{h,l\}}, K_t\}$ *solve final good producers' profit maximization problem:*

$$\max_{K_t, \{Y_{z,t}\}_{z \in \{h,l\}}} \quad Y_{l,t}^{\theta\omega} Y_{h,t}^{\theta(1-\omega)} K_t^{1-\theta} - \sum_z p_{z,t} Y_{z,t} - (1+\tau_{k,t}) r^k_t K_t$$

4. *The government runs a balanced budget:*

$$G_t = \tau_l r^m_t M_{l,t} + \tau_h r^m_t M_{h,t} + \sum_{z \in \{h,l\}} \pi_z T_t(w_{z,t} L_{z,t}) + \tau_k K_t$$

5. *All markets clear at any period t:*

$$\pi_l l_{l,t} = L_{l,t}, \quad \pi_h l_{h,t} = L_{h,t} \tag{20}$$

$$\sum_{j\in\{h,l\}} \pi_j \Big(\frac{1}{q_{t-1}} M_{j,t} + K_{j,t}\Big) = \frac{1}{q_{t-1}} \sum_{z\in\{h,l\}} M_{z,t} + K_t \tag{21}$$

$$G_t + \sum_{j\in\{h,l\}} \pi_j c_{j,t} + \frac{1}{q_t}\Big(M_{l,t+1} + M_{h,t+1}\Big) + K_{t+1} = Y_t + (1-\delta^m)\frac{1}{q_{t-1}}\Big(M_{l,t} + M_{h,t}\Big) + (1-\delta^k)K_t \tag{22}$$

4 The Optimal Taxation Problem

We solve the following optimal taxation problem. Initially, the economy is in a steady state under a status quo fiscal policy. The government then introduces a once-and-for-all change in the tax rates on low-skill and high-skill automation, τ_l and τ_h, respectively. This decision aims to optimize a Utilitarian social welfare function that assigns equal importance to the lifetime utility of both skill types while also considering the transitional dynamics. To maintain a balanced budget, the government adjusts the level of average labor income taxes during the transition toward the new steady state. That is, the government solves the following maximization problem:

$$\underset{\tau_l,\tau_h}{max} \quad \sum_{z\in\{h,l\}} \pi_z \sum_{t=0}^{\infty} \beta^t U(c_{z,t}, l_{z,t}) \tag{23}$$

such that the corresponding allocation is a competitive equilibrium for all t.

5 Calibration

This section outlines our calibration strategy and baseline results in which we solve the problem outlined in Section 4. We calibrate the model parameters in order to match some relevant aggregate and distributional features of the US economy for 2010s such that the economy is at the steady state for a given status quo fiscal policy. Some of the parameters are taken directly from the existing literature. The remaining parameters are calibrated internally as explained below. Table 1 summarizes the calibration procedure.

One period in the model corresponds to one calendar year. It is assumed that the preferences over consumption and labor supply are identical across workers and given by the following separable utility function:

$$U(c,l) = \log(c) - \phi\frac{l^{1+\nu}}{1+\nu} \tag{24}$$

The parameter ϕ, governing the disutility of labor supply, is calibrated to match the average labor supply in the US economy. The parameter ν, representing the inverse of the Frisch elasticity of labor supply, is set at $\nu = 2$, aligning it with the range commonly used in existing literature. We opt for a logarithmic utility function for consumption, reflecting a standard choice in the field of optimal taxation. The time discount factor β is calibrated to match the capital-to-output ratio in the economy.

Table 1: Calibration

Parameter		Value	Source/Target
External calibration			
τ_l, τ_h	tax on automation capital	0.05	Acemoglu et al. (2020)
τ	progressivity	0.1	Ferrière and Navarro (2018)
τ_k	tax on non-automation capital	0.1	Acemoglu et al. (2020)
π_h	fraction of high-skill workers	0.35	CPS
a_h/a_l	relative asset holdings	5.58	Kuhn and Rios-Rull (2020)
δ^k	depreciation rate of K	0.05	Greenwood et al. (1997)
δ^m	depreciation rate of M	0.19	Eden and Gaggl (2018)
$1-\theta$	income share of K	0.31	Eden and Gaggl (2018)
ν	inverse Frisch elasticity	2	literature
G/Y	government expenditures-to-GDP ratio	0.16	NIPA
$1/q$	price of automation capital	1	
Internal calibration			
β	discount factor	0.9	capital-to-output ratio=2.07
ω	income share of Y_l	0.58	wage premium=1.9
ϕ	disutility of labor supply	16.65	avg.labor supply=1/3
κ_l	productivity of M in sector-l	0.48	labor share of income=0.55
κ_h	productivity of M in sector-h	0.15	relative exposure to automation

Note: This table summarizes the calibration strategy for the model. All parameters are defined on Section 3 and Section 5. CPS and NIPA stand for the Current Population Survey of the U.S. Census Bureau (2021) and the National Income and Product Accounts of the U.S. Bureau of Economic Analysis (2021), respectively.

The status quo tax rates on automation and non-automation capital are set based on estimates by Acemoglu et al. (2020). We assume that low-and-high-skill automation are taxed at the same rate under the status quo fiscal policy. Following Acemoglu et al. (2020), we set $\tau_l = \tau_h = 0.05$, the value corresponds to average tax rate on software and capital equipment; and $\tau_k = 0.1$ which corresponds to tax rate on capital structures. Both are the values after the 2017 tax reform. The government expenditures to total output ratio is set to 0.16 based on National Income and Product Accounts (NIPA). In the optimal taxation analysis, we assume that the government finances a constant level of government expenditures given by the calibrated steady state.

Following Heathcote et al. (2017), we assume that for a given labor income level y, the labor income tax function $T(y)$ takes the form:

$$T(y) = y - \lambda y^{1-\tau} \tag{25}$$

where τ determines the progressivity of the tax system, and λ controls the average level of labor income taxation in the economy. If $\tau > 0$, the tax system is progressive; that is, it provides a redistribution from high-income workers to low-income ones. Whereas when $\tau = 0$ the tax system is neutral, and therefore, $(1-\lambda)$ stands for the linear labor income tax rate in the economy. Heathcote et al. (2017)

shows that the functional form in (25) provides a good approximation for the actual tax and transfer system in the US economy. Ferrière and Navarro (2018) provides annual estimates of τ; we set $\tau = 0.1$ based on their estimates.[13] As in Heathcote et al. (2017), the parameter λ is calibrated to clear the government budget in the initial steady state where it takes the value 0.65.

Following the relevant literature, high-skill workers are classified as those who have a college degree or above, whereas low-skill ones are those who hold less than a college degree. Kina et al. (2023) computes the fraction of high-skill workers as 0.3544 using the 2017 data of the Current Population Survey (CPS), we use their number and set $\pi_h = 0.3544$. Importantly, we also match the wage inequality between low-and-high skill workers; in the calibrated economy the wage premium equals to 1.9 as reported by Heathcote et al. (2020). We calibrate the parameter ω which governs the income share of low-skill sector output to match the wage premium.

As our environment is deterministic, the steady state asset distribution is indeterminate with heterogeneous workers. In general, the steady-state equilibrium capital holdings distribution is not unique. Hence, one should make an assumption about initial relative captial holdings across workers. Let a_l denote the capital holdings of low-skill workers, and a_h denote the capital holdings of high-skill workers such that $\pi_l a_l + \pi_h a_h = \frac{M}{q} + K$. Then for any given $x \in (0, 1)$, the steady-state is unique with $\pi_l a_l = x(\frac{M}{q} + K)$ and $\pi_h a_h = (1 - x)(\frac{M}{q} + K)$. We calibrate x to match the ratio $a_h/a_l = 5.58$ where the data moment is taken from Kuhn and Rios-Rull (2020).

The calibration of the productivity of automation capital across tasks, $\psi_z(.)$ for $z \in \{h, l\}$, is very crucial for the model to generate a realistic level of exposure to automation and labor share. Moreover, it is important to have a reasonable value of relative automation level across low-and high-skill sector. This is tricky as high-skill automation is a relatively new concept and there is no study in the literature that estimates the level of automation across skill groups. Based on the assumptions (1)-(3), we assume the following functional form for the productivity of capital across tasks and sectors:

$$\psi_z(u) = u^{-\kappa_z} - 1, \quad z \in \{h, l\} \tag{26}$$

where $\kappa_z > 0$ determines the productivity of capital in sector z.

Since there is no paper in the literature that studies the impacts of low-and high-skill automation in a quantitative set-up like in this paper, we conduct the following novel procedure to calibrate the productivity function, ψ_z. First, we calibrate the parameter that controls the productivity of capital in the low-skill sector, κ_l to match labor share of income as 0.55, where the target is taken from Hubmer and Restrepo (2021). Next, we calibrate the parameter that controls the productivity of capital in the high-skill sector, κ_h to match relative exposure to automation across skill groups using the computations of Frey and Osborne (2017) and O*NET data as follows. Frey and Osborne (2017) is a well-known and commonly cited paper in the automation literature. They estimate the probability of automation for 702 detailed occupations using O*NET data. We use their occupation set and divide it into two broad categories based on the level of education required in each occupation. More precisely, we categorize

[13] Heathcote et al. (2017) also provides estimates of τ; but since the tax function applies to capital plus labor income in their paper, we use the estimate from Ferrière and Navarro (2018) as their tax function applies only on labor income inline with the analysis in this paper.

those 702 occupations as high-skill occupations that require college degree and above and low-skill occupations that require less than a college degree using O*NET data set. Then, for each category the average level of automation probability is computed by weighting the each occupation's probability with its relative employment level. Our computations suggest that the exposure to automation in the low-skill sector is three times higher than that in the high-skill sector. We use the computed ratio as a proxy for the relative automation levels across skill groups. That is, we calibrate κ_h to ensure that in the initial steady state the fraction of tasks automated in the low-skill sector is three times higher than that of in the high-skill sector. This calibration procedure yields $\kappa_l = 0.48$, and $\kappa_h = 0.15$; and the resulting automation levels are such that in the calibrated steady state 29% of the tasks are automated in the low-skill sector ($\alpha_l = 0.29$), whereas 10% of them are automated in the high-skill sectors ($\alpha_h = 0.1$).

6 Optimal Taxation

This section documents the key features of the optimal tax reforms that we have studied. We solve for different optimal tax reforms, each characterized by a distinct set of tax instruments available to the government. This implies that in each reform, the choice variables of the government's problem, as outlined in Section 4, vary. The results are summarized in Table 2. The optimal taxes are determined by the trade-off between efficiency and equality, which in turn depends on the available fiscal instruments. Notably, a more flexible set of tax instruments can achieve a desired level of redistribution with lesser distortions compared to a more restricted set. For instance, in an environment where the Second Welfare Theorem's assumptions are met, the government has the capacity to implement individualized lump-sum taxes which allows for the maximization of aggregate welfare without introducing distortions into the economy. However, we focus on a more realistic environment where the government cannot implement either individualized lump-sum taxes or skill-type dependent labor income taxes.

6.1 A Uniform Tax Approach for Low- and High-Skill Automation

Highlighting the critical role of distinct tax treatments for low- and high-skill automation, our first step involves determining the optimal tax rate when both types are taxed equally. This involves computing the optimal automation tax under the assumption that the government is unable to distinguish between capital employed in low- and high-skill sectors, thus applying a uniform tax rate. By doing so, the government maintains the progressivity of labor income tax constant while adjusting the average labor income tax throughout the transition to ensure a balanced budget. The results are summarized in column three of Table 2.

Under this reform, the government chooses the optimal uniform tax rate on automation to maximize aggregate welfare (23), taking the transitional dynamics into account. Over the transition, the parameter λ that controls the average labor income taxation changes over time to clear the government budget for a given level of government expenditures.[14] The resulting optimal tax rate stands at 16%, a substantial increase from the pre-reform rate of 5%. This leads to a decrease in average labor income

[14] It is assumed that the level of government expenditures stays constant at its calibrated value in all of the reforms.

taxes, falling to 34% from an initial 35%. Consequently, the tax burden shifts, decreasing for low-skill workers and increasing for high-skill workers, leading to a redistribution effect.

Importantly, as the reform increases the overall taxation on automation, and hence the cost of automation capital relative to both skill types, the equilibrium automation levels in both sectors go down over the transition. The share of tasks that are automated in the low-skill sector declines to 0.26 from 0.29, and that of in the high-skill sector declines to 0.07 from 0.1. Therefore, income shares of both skill types go up. The increase in income shares mostly benefits low-skill workers as they own a lower share of the capital stock. As the reform increases the distortions on automation adoption, this generates efficiency losses. As a result, the level of output shrinks by 4.57% relative to the initial steady state. Despite the significant drop in output over the transition, the aggregate welfare increases as the reform provides a significant redistribution from some well-being from the high-skill workers (who have more capital holdings and earn higher wages) to the low-skill ones (who constitute the majority). This redistribution becomes evident when we look at the welfare gains of the reform. Our measure of welfare gains is standard as in the literature; we define the aggregate welfare gain from the reform as the constant percentage increase in consumption for all agents in the no-reform case, which yields equivalent utility to the case where the reform is implemented. The aggregate welfare gains of the reform are equivalent to increasing the consumption of both types at all periods by 0.22%. The welfare gain for low-skill workers is 1.01%, whereas high-skill workers experience a welfare loss of 1.21% in terms of consumption equivalence (CEV) units.

The reform effectively mitigates inequality in wages and consumption levels during the transition. The skill premium decreases to 1.87 from its initially calibrated value of 1.9, while the relative consumption of high-skill workers declines to 2.35 from 2.40. Although the reform leads to a reduction in both wage and before-tax labor income levels for both types, the after-tax labor income of low-skill workers experiences a relative increase of 0.92% compared to the initial steady state.

6.2 Differential Taxation of Low- and High-Skill Automation

In this section, we document the results of the reform in which the government can differentiate between the capital that is used in low-and high-skill sectors and, therefore, can implement different automation taxes. Apart from differential taxation of low- and high-skill automation, as in Section 6.1, the government maximizes social welfare (23), taking the transition to the final steady state into account. The results are summarized in column 4 of Table 2. We find that the optimal tax rates when transitional dynamics are taken into account are 23% tax on low-skill automation and 1% subsidy on high-skill automation. This leads to an overall automation taxation markedly higher than the status quo policy. Following this, there is a reduction in the average labor income tax, which settles at 34% from an initial 35%. That is, the government's optimal policy is to raise the tax on automation capital while lowering the average labor income tax, thereby generating redistribution toward low-skill workers. This approach is particularly effective given the more significant inequality in capital holdings relative to the differences in labor income.

Raising the tax rate on low-skill automation from 5% to 23% increases the cost of automation capital

Table 2: Main Results

	Status Quo	$\tau_l^* = \tau_h^*$	τ_l^*, τ_h^*	$\tau_l^*, \tau_h^*, \tau^*$
τ	0.1	0.1	0.1	0
τ_l	0.05	0.16	0.23	0.24
τ_h	0.05	0.16	-0.01	-0.05
λ	0.65	0.66	0.66	0.79
w_h/w_l	1.9	1.87	1.8	1.77
c_h/c_l	2.40	2.35	2.30	2.34
a_h/a_l	5.58	5.90	5.89	5.75
low-skill share	0.29	0.30	0.30	0.30
high-skill share	0.26	0.27	0.26	0.26
α_l	0.29	0.26	0.24	0.24
α_h	0.10	0.07	0.10	0.10
capital/output	2.07	1.98	1.98	1.99
Δ in output	-	-4.57%	-4.70%	-0.79%
Δ in w_l	-	-1.49%	-0.18%	0.54%
Δ in w_h	-	-3.30%	-5.51%	-6.17 %
Δ in labor income				
- before-tax low-skill	-	-0.55%	0.84%	5.01%
- after-tax low-skill	-	0.92%	2.18%	5.60%
- before-tax high-skill	-	-2.15 %	-4.75%	-1.56%
- after-tax high-skill	-	-0.54%	-2.93%	4.07%
welfare gains				
-aggregate	-	0.22%	0.44%	0.82%
-low-skill	-	1.01%	1.99%	1.55%
-high-skill	-	-1.21%	-2.31%	-0.49%

Note: In this table, we report the main outcomes as elaborated in Section 6. It features the initial steady-state values of the tax rate parameters and equilibrium variables in the second column, corresponding to the elements listed in the first column. The subsequent third, fourth, and fifth columns display the final steady-state values resulting from the reforms discussed in Sections 6.1, 6.2, and 6.3, respectively.

relative to low-skill labor across a wider set of tasks. This shift results in a reduction of the optimal low-skill automation level to 0.24 from an initial 0.29 during the transition. In contrast, the tax rate on high-skill automation moves in the opposite direction; the planner finds it optimal to subsidize high-skill automation at a rate of 1%, which initially pushes the optimal automation level in the high-skill sector to 0.12 from 0.1. However, as the price of capital adjusts to maintain its long-run level, the level of high-skill automation eventually returns to its initial value of 0.1.

Implementing a 23% tax on low-skill automation while providing a 1% subsidy for high-skill automation results in a notable reduction of wage inequality between skill groups. Specifically, wage inequality is reduced to 1.8 from its original level of 1.9 over the transition, a 5.33% decline. This effect is attributed to the increased tax on low-skill automation, which creates upward pressure on low-skill wages as automation capital becomes relatively more expensive. Conversely, reducing the tax rate on high-skill automation places downward pressure on high-skill wages, thereby contributing to the overall decline in wage inequality. In the model, high-to-low-skill wage ratio pins down to the following:

$$\frac{w_h}{w_l} = \Big[\frac{(1-\omega)}{\omega}\frac{(1-\alpha_h)}{(1-\alpha_l)}\Big]\frac{L_l}{L_h} \tag{27}$$

which implies wage inequality changes as a result of a change in relative automation and/or relative labor supply levels, where the term in bracket gives the relative income shares. In equation (27) the parameter ω that determines the importance of low-skill sector output in the aggregate production is fixed, whereas others are endogenously determined in the equilibrium. Decomposing the change in wage ratio into two components; relative automation levels, $\frac{1-\alpha_h}{1-\alpha_l}$, and relative labor supply, $\frac{L_l}{L_h}$, shows that the change is mostly driven by the first component such that if we keep the relative labor supply fixed at its initial steady state value, the decline in wage inequality would be 5.54%. On the other hand, if we keep the relative automation levels fixed at its initial steady state value, then the change in wage inequality would be 0.22% increase. In terms of levels, low-skill wage rate increases by 2.5% during the initial stages of the transition but then declines by 0.18% at the final steady state as the optimal policy depresses capital stock. As the government finds it optimal to subsidize high-skill automation as opposed to taxing it at rate 5% at the initial steady state, the impact on high-skill wage rate is negative throughout the transition. The high-skill wage declines by 5.5% over the transition.

Under the optimal policy, the production process becomes less capital intensive, and as a result labor share of income increases to 0.56 from 0.55. This shift is of significant importance, particularly in light of the decline in labor share of income attributed to automation technologies in recent decades. Since capital income is much more unevenly distributed relative to labor income in the calibrated economy (as in the data), any policy that increases the labor share of income is particularly important for redistribution. It is important to note that, under the production function employed in the analysis, the labor income shares are endogenous functions of the relevant automation levels. The income share of low-skill labor equals $\omega\theta(1-\alpha_l)$, and the income share of high-skill labor is given by $(1-\omega)\theta(1-\alpha_h)$. Consequently, any alteration in the automation level within a given sector has a direct impact on the corresponding labor type's income share. The optimal policy is such that over the transition, the income share of low-skill labor increases by 1%, yet that of high-skill labor stays roughly constant.

While the optimal policy yields significant redistributive benefits, it is subject to the canonical trade-off between efficiency and equality. In pursuing this balance, the government opts for production efficiency distortions to attain a more equitable distribution. During the transition, this approach leads to a reduction in total output and capital stock by approximately 4.7% and 24.3%, respectively. Consequently, while the total output shrinks, its distribution across the population becomes more equal. Under the optimal policy, which redistributes resources from high- to low-skill workers, there is a notable welfare increase for low-skill workers by 1.99% in terms of consumption equivalence units. Conversely, high-skill workers experience a welfare loss of about 2.31%. However, since low-skill workers form the larger group, the net effect is a positive aggregate welfare gain of 0.44%.

6.3 Differential Automation Taxation and Income Tax Progressivity

This section presents a summary of the reform outcomes where the government optimally selects both the progressivity of labor income taxation and differentiated automation taxes. These results are detailed in column 5 of Table 2. Under this reform, the government adopts a striking optimal policy: replacing progressive labor income taxes, $\tau = 0$, with a 24% tax on low-skill automation and a 5% subsidy for high-skill automation. This approach of allowing changing progressivity and applying linear labor income taxation significantly mitigates the distortions in the economy.[15] As a result, the final steady-state output level is only marginally lower than the pre-reform level, showing a slight decrease of 0.79%. The direction of optimal automation taxes aligns with the optimal policy in Section 6.2, aiming for redistribution from high- to low-skill workers. The implementation of automation taxes helps narrow the wage and income disparities between the worker types, reducing the need for redistributive progressive income taxes. However, the redistribution impact in this reform is comparatively limited relative to that of Section 6.2, as the removal of progressivity predominantly favors high-skill workers who have higher hourly earnings. Despite this, there is a significant welfare improvement for low-skill workers, quantified at a 1.55% increase in CEV units, while high-skill workers face a considerably smaller welfare loss than in previous reforms, at just 0.49%, culminating in an aggregate welfare gain of 0.82%.

7 Conclusion

This paper pioneers the study of optimal taxation on both low- and high-skill automation in the literature. Existing research on automation taxation has predominantly concentrated on a single type of automation technology, which typically complements high-skill workers while substituting low-skill ones. However, considering the empirical relevance of both low- and high-skill automation and their distinct effects on labor markets, this paper introduces a comprehensive general equilibrium framework that incorporates both types. The primary objective of taxation, as addressed in this paper, is to mitigate the impacts of automation on rising income inequality and the decreasing share of labor

[15] It should be noted that linear labor income taxation, where $\tau = 0$, is identified as a local optimum within the range $[0, 1]$, rather than being a global optimum.

income, phenomena extensively documented in empirical studies. Our findings indicate that an optimal governmental approach involves taxing low-skill automation at a rate of 23%, and conversely, subsidizing high-skill automation at 1%. This strategy aims to narrow the gaps in wage and income distribution. Consequently, while overall output experiences a contraction, the result is a reduction in consumption and wage inequality, accompanied by an increase in the labor share of output.

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