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AI, Automation and Taxation

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Abstract: This chapter examines the implications of Artificial Intelligence (AI) and automation for the taxation of labor and capital in advanced economies. It synthesizes empirical evidence on worker displacement, productivity, and income inequality, as well as theoretical frameworks for optimal taxation. Implications for tax policy are discussed, focusing on the level of capital taxes and the progressivity of labor taxes. While there may be a need to adjust the level of capital taxes and the structure of labor income taxation, there are potential drawbacks of overly progressive taxation and universal basic income schemes that could undermine work incentives, economic growth, and long-term household welfare.

Keywords: AI, Automation, Inequality, Labor Share, Optimal Taxation, Tax Progressivity

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1. Introduction

The digital transformation of the economy and, more recently, artificial intelligence (AI) are catalyzing profound changes in labor and capital markets. A growing research literature addresses a wide range of outcomes, such as productivity growth, industry concentration, the future of labor, income inequality both among workers and between workers and capital owners, and what the appropriate policy responses are. Despite these efforts, there remains considerable uncertainty about how the economy will be affected by AI and the broader trend toward automation in the production of goods and services.

This chapter analyzes the implications of AI and automation on the taxation of labor and capital in advanced economies. The analysis begins with a review of the small but rapidly growing empirical research literature on the effects of AI on key economic outcomes such as the displacement of workers, productivity growth and income inequality. We then examine what the theoretical research on the optimal taxation of labor and capital income says about this changing labor market landscape. Finally, we discuss the implications of the empirical and theoretical findings for tax policy.

Although there is still considerable uncertainty about the full extent of the effects of new AI and automation technologies, there are three important implications for the economy that are relevant for taxation: (i) a potential increase in the share of capital income in total national income; (ii) a change in the distribution of returns in the labor market, as some workers become more productive while others face lower wages or unemployment; and (iii) a change in the distribution of returns in the capital market, as new technologies generate substantial gains for firms and investors that successfully exploit new innovations and capture large market shares, leaving others behind.

The first implication suggests that there may be a shift in the balance from labor to capital taxes if governments need to maintain revenues to finance investment and redistribution between capital owners and workers. The second and third implications call for adjustments in both the structure of labor income taxes and transfers (such as changes in the marginal tax schedule) and the structure and composition of capital taxes (such as changes in the reliance on different types of capital taxes or changes in the rate structure).

It is essential that governments provide appropriate incentives for entrepreneurship, innovation and investment in productivity-enhancing technologies. These activities generate new products and services, as well as jobs and income, and are therefore central to economic growth. If the government needs to raise more revenue and redistribute income and wealth, it must balance these policies against the efficiency costs of taxation. However, higher income growth also allows governments to redistribute more, even if taxes remain unchanged, by financing transfers and publicly subsidized social services that have important equalizing effects.

There are also other aspects of AI and automation that affect the tax system. For example, if these technologies facilitate international labor and capital mobility, this may require coordination of tax policies across countries. New technologies may also affect how individuals and firms respond to taxation, for example by increasing the transparency of tax laws or improving the reporting of income, which may require adjustments to the tax system for efficiency purposes.

2. Empirical Findings on AI and Automation

There are still relatively few empirical studies analyzing the impact of AI and automation on Western economies.[1] Acemoglu and Autor (2011) provided an early overview and analytical framework showing how the links between technological change, the skill distribution of workers, and the return to capital affect employment, income, and overall welfare. In this section, we discuss the most recent empirical literature on the economic effects of AI and the links to taxation.

2.1 The End of Labor?

A central question in the debate about AI and automation is how these technological developments will affect the need for workers. Researchers and policymakers alike have debated whether AI and automation mean the end of work as we know it. Some projections suggest a future in which humans will no longer be needed to produce food, energy, and consumer goods once robots, or bots more generally, do it both cheaper and better.

Fear of technological change is not a new phenomenon. A recurring concern throughout history has been that technological progress will lead to widespread replacement of workers by machines, creating unemployment and greater inequality. The Luddite riots of the 19th century were directed against the spread of machines and automation, and in 1930 John Maynard Keynes warned of what he called “technological unemployment”.[2] With the benefit of hindsight, we know that these fears were exaggerated. Mechanization in the 19th and 20th centuries did not impoverish workers. Although some human tasks were replaced, the innovations created entirely new sectors of the economy and job opportunities beyond traditional occupations.

In a study of how AI has affected the labor market in the 21st century, Acemoglu et al. (2020) analyze online job postings in the United States during the 2010s. They document a significant increase in AI-related job postings during this period. The increase has occurred primarily in firms that perform tasks related to AI capabilities, and these firms have also seen a noticeable decline in hiring for non-AI jobs. The study also observes a shift in demand toward the specific skills needed to work with AI. Despite these significant changes at the firm level, the study found no overall effect of AI on employment or wage growth in the economy.[3]

Predicting when the latest developments in AI and automation will lead to major disruptions in the labor market is difficult, as we are still in the early stages of this technological evolution. In the OECD’s most recent employment outlook (OECD 2023a), the organization found little evidence of AI’s impact on the labor market, although certain segments showed some traces in the demand for certain skills and tasks, consistent with the findings of Acemoglu et al. (2020). In the US and Germany, overall unemployment fell after the 1990s, and in France it has been stable since the early 1980s. For the OECD, there is no discernible trend in unemployment rates over the past 20 years. Nevertheless, the OECD expects AI to have a profound impact on the entire labor market in the coming years, as it can be seen as a general-purpose technology that affects all levels of production.

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[1] For two comprehensive treatments of the role of AI for developed economies, see Agrawal et al. (2019, 2022).
[2] See Mokyr et al. (2015) for the sources of these quotations and a fuller discussion of their historical and cultural context.
[3] A similar positive effect on AI-related occupations and tasks has been found in a study of online job postings in several European countries (Duch-Brown et al. 2022) and in the German labor market over the past two decades (Engberg et al. 2023).

Another possible channel through which AI and automation may erode the role of labor in the economy is the declining labor share of national income. The labor share indicates the relative importance of labor costs in the production process compared to the return to owners of capital. Even if AI and automation do not increase unemployment, these new technologies could make workers less valuable in the production process, depressing wages, and labor income in favor of robots and AI processes.

Several studies have discussed and proposed explanations for the evolution of labor and capital shares in OECD countries, some of them emphasizing the role of automation and other forms of labor-saving technological change (Acemoglu and Restrepo 2019). However, it is fair to say that no consensus has been reached in the empirical work on the evolution of labor shares. Although several papers have argued that labor shares are on a downward trend in Western economies, especially in the United States, the magnitude of this decline is debated and the underlying explanations seem inconclusive (Karabarbounis and Neiman 2014; Rognlie 2016; Grossman and Oberfeld 2022).

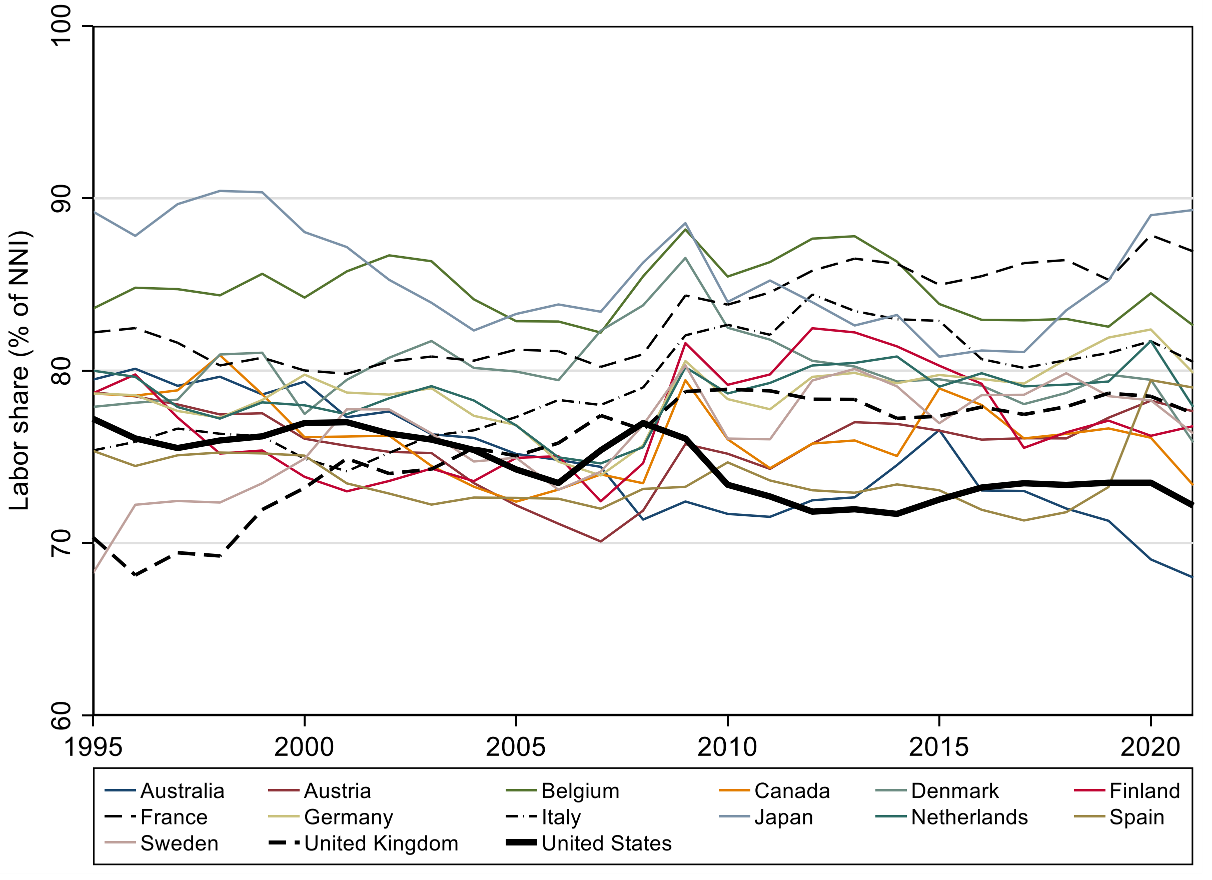
Figure 1 shows the most recent data on labor shares in a sample of OECD countries over the past 25 years. The figure shows the labor share of net national income excluding capital depreciation, which is the part of capital income that must be spent on maintenance to keep the capital stock intact.

The main stylized pattern that emerges from the figure is that the labor share has been relatively stable in most OECD countries over the past 25 years. The labor share in these countries ranged from 70 to 90 percent of national income in 1995 and is similar in 2021.[4] In some countries, notably the United States, a decline can be observed. In some other countries, such as France, Italy, and the United Kingdom, the labor share appears to have increased over the period. The overall message, however, is the absence of a pronounced secular trend in the labor share during the period of AI and automation in Western economies. If anything, the cross-sectional variation in the labor share across countries is much larger than its time-series variation within countries over time.[5]

[4] In fact, net labor shares in these countries were also in the range of 70 to 90 percent in 1960.

[5] Figure 1 shows the labor share of national income, excluding capital depreciation costs due to technological wear and physical deterioration of assets. Research often includes these depreciation costs and shows a steeper decline in labor shares over time due to increasing depreciation from technological progress. However, many inequality studies prefer to exclude depreciation to better reflect capital income available for investment or consumption by owners (for example, Piketty 2014; Rognlie 2015).

Figure 1: Labor Share of National Income in OECD countries, 1995–2021



Note: The graph shows labor shares net of capital depreciation.
Source: AMECO, European Commission.

The stability of labor shares in OECD countries, despite the documented developments in AI and automation technologies, is interesting and could have several explanations. One is that there are complementarities between capital and labor income. For example, if enough workers become more productive along with AI investment, the labor share may well remain unchanged despite the increasing presence of AI. Another explanation could be that higher capital investment in AI and automation is offset by lower marginal productivity of other capital inputs, as would happen in a Cobb-Douglas production technology. In such a case, the capital share does not change despite new investments in AI technologies. It should also be noted that the development of generative AI is still in its early stages, and the impact of AI on the economy is expected to grow in the coming years. Whether this development will also affect the shares of labor and capital in national income remains to be seen.

2.2 Productivity Growth

Technology is widely regarded as the primary source of economic progress, and many believe that AI and automation technologies are paving the way for significant resource-saving advances. The result is not just an increase in productivity, but a sustained acceleration in economic growth. However, we still know relatively little about the extent of these growth effects of AI and automation. Futurist Roy Amara famously said in the 1970s that "people tend to overestimate the short-term impact of new technologies while underestimating their long-term effects." Robert Solow made a similar point after studying the growth effects of computers in the 1980s: "You can see the computer age everywhere but in the productivity statistics."[6]

There is a lack of empirical research on the impact of AI and automation on productivity in advanced economies. A recent report suggested that generative AI could increase global GDP by seven percent, which must be considered a large boost from a single technological innovation.[7] However, the broader impact of AI on productivity and growth remains shrouded in uncertainty.

The study by Brynjolfsson et al. (2023) examines the incremental deployment of a generative AI tool designed for conversational assistance in customer support contexts. The study finds that the AI tool improves productivity, as evidenced by a 14 percent increase in resolved issues per hour. Another study (Noy and Zhang 2023) explores the productivity implications of generative AI technology, specifically the ChatGPT chatbot, for mid-level professional writing tasks. Through a carefully controlled online experiment, they found that ChatGPT significantly improved productivity, reducing average task completion time by 40 percent and improving work quality by 18 percent.

Higher income growth from AI and automation could also have implications for taxation. It could either allow policymakers to lower income tax rates without changing revenues, which in turn could further boost productivity growth through incentive effects. Alternatively, tax revenues could rise with tax rates unchanged, allowing governments to spend more on either consumption or investment. To the extent that this spending is directed towards publicly subsidized social services or cash transfers, this would also have a clear distributional impact, as these have been shown to be highly progressive in nature (Verbist et al. 2012).

2.3 AI and Tax Administration

Many people believe that AI has the potential to improve the efficiency of both tax administration and taxpayer compliance. The cost of administering and complying with tax systems in rich countries is not trivial. Collecting taxes and auditing taxpayers costs about 0.5 percent of GDP, while corporate compliance costs are more than twice as high, estimated at 1.3 percent of GDP in a recent EU study.[8]

Tax authorities in several countries have started using chatbots to handle common queries. This shift provides round-the-clock service availability, freeing up human agents to deal with other issues. AI-powered machine learning can also improve audit processes. By identifying patterns of non-compliance and potential fraud, tax authorities can optimize the allocation of audit resources. In addition, generative AI tools can transform back-office functions, from analyzing the impact of policies to assisting with hiring and modernizing legacy systems.

AI is also impacting tax compliance and accounting routines. Automating mundane tasks such as data entry and reconciliations can save resources, and automating the tracking and analysis of regulatory updates allows companies to stay compliant and reduce the risk of penalties. Machine learning algorithms are also being used to learn from historical audits, which can improve the audit process. A study on the impact of AI on audit quality and efficiency (Fedyk et al. 2022) analyzed 310,000 comprehensive resumes from the top 36 audit firms in the US.

[6] For sources, see the Wikipedia entries on "Amara's Law" and "Productivity Paradox".
[7] Goldman Sachs (2023).
[8] See OECD (2023b) and European Commission (2022).

The results suggest that investment in AI contributes to higher audit quality and lower fees, while also gradually replacing human auditors over a period of years.

2.4 Income Inequality

The distributional impact of AI and automation is highly uncertain ex ante. A recent review of the theoretical literature by Korinek et al. (2021) shows that the direction of the change in inequality depends on several parameters, such as whether the technology is unskilled or skilled labor-saving, whether additional capital accumulation is complementary to labor, or whether there is scarcity of certain factors of production.

In an early study of the distributional effects of computer technology, Autor, Levy, and Murnane (2003) examine how the relative earnings and labor supply of different occupations within firms have been affected. Their main finding is that while the relationship between CEOs and janitors has been largely preserved, a significant segment of middle-level office jobs has been displaced. The advent of computers and information technology systems may thus have increased income inequality, but by making high-skilled workers even more productive, low-skilled jobs receive a lower relative return or are even pushed out of the production process altogether. The main channel of automation proposed by the authors is that routine tasks typically associated with middle-income positions are gradually disappearing, creating a polarization of the labor force into high- and low-income segments. However, Autor (2024) points out that AI may in fact increase the productivity of middle-skilled workers performing routine tasks, if these are the kinds of tasks that can be performed more efficiently thanks to AI. In this way, the wages and incomes of these middle-skilled workers rise disproportionately, offsetting the polarizing tendencies in the labor market associated with earlier automation developments.

Another study, Doorley et al. (2023), examines the impact of increased robot adoption on income inequality in 14 European countries from 2006 to 2018, coinciding with a surge in industrial robot adoption. The study finds that automation led to a decline in both relative hourly earnings and employment rates among the most affected demographic sectors, mirroring findings observed in the United States. By incorporating the effects of robotic wage and employment disruptions into the EUROMOD microsimulation model, the study concluded that the impact of automation on income inequality was minimal. It emphasizes that the diversification of household labor income and the implementation of tax and welfare policies effectively mitigate the adverse effects of automation-induced labor market disruptions. In addition, transfer policies were found to have been crucial in buffering the impact of these disruptions on household incomes.

Two recent studies examine how the introduction of AI tools affects workers' efficiency. Both studies analyze relatively academic tasks and compare the effects on high- and low-skilled workers. The results clearly suggest that AI reduces inequality in productivity or real wages among workers. Brynjolfsson et al. (2023) find that almost all of the observed population-wide productivity gains occur among inexperienced and low-skilled workers. In contrast, experienced and highly skilled workers were barely affected. Noy and Zhang (2023) study the application of generative AI technology to academic writing tasks. They find positive overall productivity effects of AI, and also that the productivity gains of workers are larger for the low-skilled than for the high-skilled. In other words, certain forms of AI appear to be labor-enhancing, and complementary to the tasks and performance of less experienced workers.

How capital income inequality, or wealth inequality more broadly, will be affected by AI technologies has not been widely studied. The impact of AI on financial investment and wealth management has been documented by Shanmuganathan (2020) in an analysis of the use of new software and the adoption of AI. However, everyone could benefit from access to such advanced investment software, and whether these benefits will be skewed toward high- or low-skilled investors is an open question.

Industry concentration effects could change capital income inequality. For example, AI may lead to new superstar firms and a higher overall concentration of corporate profits, making capital incomes more skewed. However, if the owners of these firms are low-income earners, perhaps primarily workers with pension funds who are major stakeholders in the new AI superstar firms, then the ultimate impact on disposable income inequality is less obvious. More research is therefore needed on these outcomes.

3. AI, Automation, and Optimal Taxation

In analyzing how taxes will be affected by AI and automation, the natural starting point is the theory of optimal taxation of labor and capital income. In this section, we first outline the basic structure of assessing the optimality of tax systems, and then contextualize recent research on these topics as it applies to the adoption of AI and automation technologies.

3.1 The Theory of Optimal Income Taxation

The optimal income taxation literature builds on Mirrlees (1971) and emphasizes information as the key constraint on tax policy. The government wants to redistribute among individuals with different earning abilities, but it cannot observe these abilities for tax purposes, so it must use observable quantities instead. Since labor income accounts for most of the income in the economy, the literature has focused mainly on the design of optimal labor income taxation and how capital taxes can usefully complement optimal labor income taxation.[9]

The earlier literature debated whether taxing labor income alone was sufficient for redistribution or whether taxing capital income as well was justified. The analysis of Atkinson and Stiglitz (1976), Judd (1985), and Chamley (1986) suggested that capital should not be taxed because capital taxes would distort both labor supply and intertemporal consumption decisions.

More recent research has qualified this conclusion, showing that capital taxes can be useful for both equity and efficiency reasons, and has challenged some of the assumptions of the earlier literature.[10] For example, higher taxes on labor income than on capital might discourage human capital accumulation, as suggested by Jacobs and Bovenberg (2010), or lead to an overreliance on automation, as discussed by Acemoglu, Manera, and Restrepo (2020). A significant gap between the taxation of capital and labor income could also incentivize income shifting, a concern raised by Pirttilä and Selin (2011) and Harju and Matikka (2016). Moreover, advances in international cooperation among tax authorities and various tax enforcement strategies have increased the ability of governments to effectively tax mobile capital income. These measures reduce the likelihood of income and asset offshoring in response to capital income taxation, as noted by O'Reilly, Parra Ramirez, and Stemmer (2019) and Menkhoff and Miethe (2019).

[9] Here we limit ourselves to discussing the choice between taxing labor income and taxing capital income, and abstract from the question of whether to tax income or expenditure (consumption).
[10] Bastani and Waldenström (2020, 2023) review the arguments for capital taxation and compare wealth and capital income taxes.

One of the main efficiency arguments in favor of capital taxes is related to the fact that progressive labor income taxes aim to redistribute income from high-skilled (high-income) workers to low-skilled (low-income) workers, but this creates incentives for high-income workers to reduce their labor supply and mimic low-income workers in order to pay lower taxes (referred to as "mimicking" in the optimal tax literature). If mimicking workers save more than genuine low-income workers, then capital taxes can discourage mimicking and make the labor income tax more efficient. The intuition is that if workers save to be able to afford to work less in the future while enjoying more leisure and paying lower taxes, it is optimal to tax savings.

One of the main equity arguments in favor of capital taxes is that individuals not only differ in their ability to earn labor income, but also face different rates of return on their investments (as empirically documented, for example, by Fagereng et al. 2020 and Bastani et al. 2024) or have different levels of wealth, leading to heterogeneity in capital income conditional on labor income. Capital taxes then redistribute income between individuals with different rates of return or different levels of wealth who have the same labor income. Thus, capital taxes provide redistribution that labor taxes cannot.

An important question is whether taxes can be non-linear (progressive) or must be linear (proportional). In many countries, labor income is observed at the individual level because employers report it to the tax authorities (see Kleven et al. 2011). Thus, nonlinear taxes on labor income are usually feasible. However, nonlinear taxes on capital are more difficult to implement and are usually proportional. This is due to tax arbitrage and the difficulty of verifying the identity of the saver. Another important issue is the extent to which the government can use past earnings to determine the current tax burden. Pension systems are typically history-dependent in the sense that pension benefits depend on contributions over a working life, but history-dependence in the income tax system is much rarer. The optimal taxation of capital may depend crucially on whether or not the underlying tax system is allowed to be history dependent.

3.2 The Role of Changing Inequality in Labor and Capital Markets

Standard optimal tax theory shows how, for a given social objective function, the tax structure on labor income should depend on the distribution of labor productivity and on taxable income elasticities, which capture behavioral responses to taxation. This standard model assumes that individuals differ only in their labor productivity and that technology is linear in labor inputs, so that the wage distribution is fixed. If automation and AI change the labor productivity distribution, policymakers can respond by calculating a new labor income tax structure based on an updated labor productivity distribution. In this way, the impact of a changing labor productivity distribution can be assessed within the standard optimal tax framework.[11]

Recent studies also show how to assess the impact of changes in the distribution of capital returns on optimal taxation. Simulations in Gerritsen et al. (2022) show that the shape of the distribution of capital returns affects optimal taxes on capital income. For their baseline calibration, they find that most individuals face higher optimal taxes on capital income than on labor income when the rate of return to capital depends on the amount saved (scale-dependent returns), but not when capital returns are correlated with labor productivity (type-dependent returns). Thus, an important policy question is how automation/AI affects the heterogeneity of returns, whether it increases returns to skill or exacerbates scale effects.

[11] See Miao (2022) for a thorough investigation of how optimal income tax schedules depend on the shape of the underlying skill distribution.

3.3 Implications of an Endogenous Wage Distribution

A key issue is that tax policy can affect the distribution of returns in labor and capital markets. We now turn to optimal tax models that endogenize the *wage* distribution. However, we find that there is a lack of models that can tractably handle optimal taxation with heterogeneous and endogenous returns to *capital*.

Stiglitz (1982) is one of the first papers to study optimal income taxation with an endogenous wage distribution. He develops a simple model in which the relative wages of low- and high-skilled workers are determined by the relative supply of low- and high-skilled labor in the economy. He shows that if high-skilled labor increases the productivity of low-skilled labor, it may be optimal to subsidize the income of high-skilled labor. Thus, the government creates a distortion for high-skilled agents to achieve redistribution through the wage channel, reducing the need for distortionary labor income taxation.[12]

Naito (1999) studies optimal income taxation with several sectors of the economy that have different production functions. He shows that if the relative demand for different types of labor (and hence relative wages) varies with the demand for different goods, then production efficiency is not optimal. He argues that it may be optimal to subsidize goods produced by low-skilled workers, or to have public enterprises employ low-skilled workers, to create a scarcity of low-skilled labor and thereby achieve a more equal distribution of wages. In this way, the government distorts consumer or producer prices to allow for more efficient redistribution through progressive taxation of labor income, contrary to the classical results of Atkinson and Stiglitz (1976) and the production efficiency results of Diamond and Mirrlees (1971).

These papers help us understand the implications of automation and AI for optimal taxation, which operate through changing wage distributions. Note that the distribution of wages depends not only on the relative supply of different types of labor, but also on capital inputs, which have different complementarities with different types of labor. Thus, in general, if a capital input is more complementary to high-skilled labor than to low-skilled labor, it may be optimal to tax it in order to compress wages and thereby reduce the redistributive pressures of the income tax system.

3.4 Taxing Robots

Several recent papers have quantified the optimal tax rates on different types of capital and the associated welfare gains. It is worth noting that if specific taxes on certain capital inputs are introduced, such as robot taxes, their benefits must be balanced against potential classification problems for different types of capital inputs and coordination problems across countries. We therefore discuss papers that assume that specific taxes on automation and AI are not feasible.

An early contribution investigating the impact of automation and AI on optimal taxation is Slavík and Yazici (2014). They study the optimal taxation of capital in a model with equipment capital and structure capital. They find that it is optimal to tax equipment capital at a higher rate than structure capital, because equipment capital is more complementary to high-skilled workers than to low-skilled workers. By taxing equipment capital more, the government can reduce the wage gap between high- and low-skilled workers and increase the labor supply of both groups. In a quantitative version of the model, they find that the optimal tax rate on equipment capital is at least 27 percentage points higher than the optimal tax rate on structural

[12] Rothschild and Scheuer (2013, 2014) extend Stiglitz (1982) by allowing for multidimensional heterogeneity and sectoral choice. See also Sachs et al. (2020).

capital during the transition and in the steady state. Furthermore, they find that the welfare gains from optimal differential capital taxation are about 0.4 percent of lifetime consumption.

More recently, Guerreiro, Rebelo, and Teles (2022) build on the model of Slavík and Yazici (2014) by introducing technological progress and endogenous skill acquisition. They examine the impact of a sustained decline in the cost of automation on income inequality, given the current U.S. tax system. They show that workers performing routine tasks are displaced by robots and face lower wages and job opportunities, while workers performing non-routine tasks benefit from automation. They find that it is optimal to tax robots while the current generations of routine workers, who cannot move into non-routine occupations, are still in the labor force. Once these workers retire, the optimal robot tax is zero. This is because taxing robots mitigates automation by reducing the income loss and borrowing constraints of displaced workers, while increasing the labor supply of non-routine workers who benefit from automation.

From a static optimal income taxation perspective, Thuemmel (2023) analyzes the optimal taxation of robots, other capital, and labor income. In contrast to Guerreiro, Rebelo, and Teles (2022), who consider only one type of non-routine worker, he considers three types of workers: non-routine cognitive, non-routine manual, and routine. He also introduces wage heterogeneity within each occupation. Thuemmel (2023) shows that it is optimal to distort robot adoption and that the tax (or subsidy) exploits general equilibrium effects to compress wages, which reduces the income tax distortion of labor supply and thereby improves welfare. In the calibrated model, a robot subsidy is optimal when robots are expensive. As robots become cheaper, it becomes optimal to tax them. However, if the status quo tax system is reformed, most of the welfare gains can be achieved by adjusting the income tax. The marginal gains from taxing robots differently from other capital goods are negligible.

A problem with the above papers is that the results may be sensitive to the structural assumptions that govern how the wage distribution is affected by technology. Costinot and Werning (2023) investigate how optimal taxes on new technology firms depend on changes in the wage distribution due to new technology. Their work derives optimal taxes on new technology firms as a function of a few sufficient statistics that can be estimated empirically with minimal structural assumptions. Using empirical estimates of these statistics, they show that small, positive robot taxes are optimal, although the welfare gains from such taxes are small when income taxes are optimally set. They also identify a set of conditions under which the optimal robot tax decreases as automation progresses. Of course, these sufficient statistics are only valid when considering marginal changes to the current equilibrium of the economy, which limits their applicability.

The above papers assume that robots and new technologies can be taxed. However, this is challenging due to classification problems, which means that taxes on robots or new technologies, while potentially attractive in theory, may be difficult for governments to implement. Therefore, it is important to also consider the optimal tax implications of automation and AI under the assumption that such specific taxes are not feasible.

Loebbing (2022) assumes that robots cannot be taxed and analyzes how progressive tax reforms can affect the direction of technological change and reduce the wage gap between high and low earners. The main idea is that when taxes are more progressive, low-skilled workers have a stronger incentive to work than high-skilled workers, which induces firms to adopt and use technologies that are more suitable for low-skilled workers. These effects of tax reforms on technology choice make the optimal tax system more progressive, with higher marginal tax rates for high earners and lower rates for low earners.

Another paper that assumes that different types of capital cannot be taxed differently is Kina et al. (2024). They study the optimal taxation of capital and labor income in an incomplete market model with capital and skill complementarities. They show that it is optimal to rely more on taxes on capital income and less on taxes on labor income when capital and skill complementarities are taken into account. In their model, individuals face idiosyncratic wage risk and the government redistributes using a nonlinear tax on labor income (with a specific functional form) and a proportional tax on capital income. The optimal capital income tax rate is 60%, which is significantly higher than the optimal rate of 48% in an identically calibrated model without capital-skill complementarity.

While the above papers are concerned with optimal tax systems, there is also a literature on how to reform current income taxes in response to changes in technology. Schulz, Tsyvinski, and Werquin (2023) study the challenge of re-optimizing the tax system to redistribute resources from winners to losers after major economic disruptions. They derive a formula for the compensating tax reform that takes into account skill complementarities in production and exhibits progressivity. They quantify the income losses caused by robots and show how a compensatory reform can effectively mitigate the negative effects of automation.

4. Implications for Tax Policy

Tax policy is a powerful tool that governments can use to address the adverse economic consequences of new technologies such as AI and automation. The previous sections discussed empirical and theoretical aspects of these issues, and in this section, we continue with a discussion of their implications for tax policy.

4.1 The Balance between Labor and Capital Income Taxes

If AI and automation lead to a declining share of labor in national income, as some scholars argue, and if labor income is taxed at a lower rate than capital income, as it is in most advanced economies, then AI and automation will lead to a decline in tax revenues, all else equal.[13] Here, standard tax logic suggests raising the capital income tax rate to keep tax revenues unchanged.

However, the available empirical evidence does not point to a sharp decline in the labor share in OECD countries in recent years, with the notable exception of the United States, where it has declined somewhat. Therefore, in the absence of a clear shift in the balance between labor and capital income in response to the new technologies analyzed here, this does not motivate a need to change the balance between labor and capital income taxes.

4.2 The Progressivity of Labor Income Taxation

It is likely that AI and automation will change the skewness of the productivity distribution in the labor market. However, the direction in which this will happen is not clear. Some analyses find that inequality decreases after the introduction of AI in the production process. The reason is that AI primarily makes low-skilled workers more productive, while the impact on high-skilled workers is less evident. Some studies have found evidence of displacement of low-skilled workers when firms invest in AI.

[13] For an analysis of effective taxation of labor and capital income in OECD countries, see Hourani et al. (2023).

Optimal tax theory suggests that if the productivity distribution becomes more skewed, this justifies a more progressive income tax schedule. Of course, such an increase in progressivity must be balanced against the disincentive effect of higher marginal tax rates, which dampens incentives and hampers income growth.

Transfers perform a crucial distributional role in the tax and transfer system that should not be overlooked when discussing tax policy responses to AI and automation. Several studies show that public spending plays an important role in overall income redistribution, providing tax-financed cash transfers and in-kind social services such as schooling, health care, or care for the elderly. These transfers and in-kind services disproportionately benefit low-income households and equalize income and wealth.[14] If AI and automation increase economic growth, which raises average incomes, as some studies suggest, and tax rates remain unchanged, then tax revenues will increase as a result. This, in turn, will allow governments to spend more on publicly subsidized social services that disproportionately benefit low-income households and equalize income and wealth.

Universal Basic Income (UBI) is a specific type of transfer policy that is sometimes mentioned in the context of policies to address the threats posed by AI and automation. UBI aims to protect displaced or not-yet-displaced workers from persistent income shocks by providing all adult individuals with a flat grant based on citizenship. While this form of income protection is not entirely orthogonal to the universal coverage of most European welfare systems, it differs in that it is a much more expensive policy. Moreover, it is likely to have large, negative effects on long-term productivity and welfare by reducing the incentives to study and work among broad segments of the population. Perhaps in the very long run, when the need for human labor is substantially reduced, some form of UBI offering a combination of in-kind benefits and cash transfers may be the only sensible policy. But we think that is a long way off.[15]

4.3 The Structure of Capital Taxation

There has been little empirical analysis of the role of AI and automation on industry concentration, corporate profits, capital income, and wealth. Higher industry concentration could arise if investment becomes increasingly capital intensive and access to large data sets creates natural monopolies. To the extent that such increased industry concentration leads to greater inequality in capital income, some optimal tax models suggest the introduction of progressive capital taxation. Indeed, if all income consists of capital income, the only way to achieve any redistribution at all is to redistribute capital income.

However, the effectiveness of progressive tax systems depends on information-gathering technologies and measures to prevent tax arbitrage. A key issue is how ownership of firms that compete successfully and benefit from new technologies is distributed across the population. In addition to direct redistribution of capital income and wealth, the government can promote more egalitarian ownership shares by encouraging stock ownership or pension systems that invest in firms that specialize in new technologies.

Digital taxes have been proposed as a way for governments to deal with the increasingly international dimension of economic activity and corporate profits. New technologies are at the heart of this development, and the OECD has recently developed a framework, Pillar One, that aims to shift corporate taxes from countries where companies are registered to countries where

[14] See, for example, Verbist et al. (2012) and Aaberge et al. (2019).
[15] See Hoynes and Rothstein (2019) for a discussion of UBI for the U.S. and other advanced economies.

their products and services are sold. This legal framework is not yet in place, and it is not certain how important it will be in the coming years, but it reflects how tax policy is responding to the new realities dictated by technology.

Robot taxes are a specific form of capital taxation that has been discussed to slow down the excessively labor-saving aspects of AI and automation technologies. Some optimal tax models propose taxes on specific capital inputs, robots, to achieve this goal. However, it remains unclear how a robot tax should be implemented in real life, as it involves drawing dividing lines between similar technologies. Moreover, to the extent that AI and automation increase the overall productivity of the economy, there is a general growth argument against implementing such taxes. There is an important interplay here between taxation, regulation, and how such tax and regulatory policies are coordinated across countries. The conclusion is therefore that robot taxes do not seem to be a plausible part of a well-designed tax system in the near future.

4.4 Occam's Razor: The Limits of Tax Policy in Addressing AI and Automation Challenges

While tax and transfer policies are undeniably powerful tools at the government's disposal to shape economic outcomes, they are not a panacea for all the challenges posed by AI and automation. In this context, the principle of Occam's Razor suggests the merit of designing policies that directly target the specific problem at hand.

For example, increasing industry concentration could be more effectively addressed by revising regulatory barriers to entry and implementing competition policies to curb unlawful collusion. In the field of AI, monopolistic control over data, which leads to monopoly rents and inefficiencies, may be better addressed through data regulation rather than tax policy. Moreover, education policy could serve as a crucial tool to respond to shifts in the labor market's valuation of different skills. In addition, in scenarios where the capital share of income is rising, encouraging broader ownership of business capital among the general population could serve as an important countermeasure.

4.5 Barriers to AI adoption: When Gains Become Too Unequally Distributed

While AI may be economically beneficial overall, it affects different groups in different ways. Some groups may be negatively affected, especially during periods of production restructuring. The development of AI technologies, and automation more broadly, depends on political decisions and may therefore ultimately depend on the support of the majority of the population. Negative outcomes for certain groups may reduce political support for pro-AI policies. Although strong opposition to AI based on the perception that its benefits will not accrue to all may seem remote, an increase in income inequality, whether as a result of AI or automation, may well lead to anti-technology demands that would be negative for advanced economies.

The good news is that the likely productivity gains from AI also create economic space for society to compensate these vulnerable groups or support the transition in various ways. A key principle of such policies is to protect individuals, not specific jobs or industries, especially since reallocation is in many cases the very basis of the gains generated by AI processes. In this way, the fundamentally positive technological development can continue to promote development and prosperity, despite the fact that it may also have a negative impact on the incomes of certain groups.

5. Concluding Remarks

Predictions about how AI and automation will reshape the economic landscape veer between optimism and disillusionment, and great caution is warranted in interpreting them. There is indeed a compelling case to be made for considering the transformative capacity of AI, which brings with it intelligent attributes such as learning, reasoning, and problem solving. The productivity boost from AI is expected to increase global growth rates by an order of magnitude. At the same time, AI and automation may also have a negative impact on the groups of workers who lose out in the competition with new generative AI tools. AI may also widen the gap between capital owners and workers, leading to inequality and tensions in society, with potentially negative effects on cohesion and social stability.

Tax policy provides a direct avenue through which governments can address the economic consequences of AI and automation. In this analysis, we have discussed both the conceptual implications from the theory of optimal taxation and reviewed the small but rapidly growing empirical research literature on the subject.

Our analysis provides some preliminary insights. If AI and automation lead to a significant increase in the share of capital in national income, there may be a need to shift the tax balance more toward capital taxation. While such an increase has not yet been observed in most advanced economies, many researchers expect it to occur in the future. Another conclusion relates to the potential for new technologies to exacerbate labor income inequality. This scenario could justify more progressive income tax systems. However, it is important to recognize that higher marginal tax rates can undermine incentives and income growth. Given that a significant part of redistribution is achieved through tax-financed transfers and in-kind benefits to low-income workers, excessive progressivity could prove detrimental from both efficiency and equity perspectives. Moreover, current research provides little support for tax and transfer policies specifically designed to mitigate the effects of AI and automation. Proposals such as robot taxes or universal basic income are likely to disadvantage households in both the short and long term and are not advisable for the foreseeable future.

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