INTERNATIONAL MONETARY FUND

STAFF DISCUSSION NOTE

Broadening the Gains from Generative AI: The Role of Fiscal Policies

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SDN/2024/002

2024
JUNE

 SDN/2024/002

IMF Staff Discussion Notes
Fiscal Affairs Department

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Authorized for distribution by Vitor Gaspar
June 2024

ABSTRACT: Generative artificial intelligence (gen AI) holds immense potential to boost productivity growth and advance public service delivery, but it also raises profound concerns about massive labor disruptions and rising inequality. This note discusses how fiscal policies can be employed to steer the technology and its deployment in ways that serve humanity best while cushioning the negative labor market and distributional effects to broaden the gains. Given the vast uncertainty about the nature, impact, and speed of developments in gen AI, governments should take an agile approach that prepares them for both business as usual and highly disruptive scenarios.

Recommended Citation: Brollo and Others. 2024. "Broadening the Gains from Generative AI: The Role of Fiscal Policies." IMF Staff Discussion Note SDN2024/002, International Monetary Fund, Washington, DC.

ISBN:	979-8-40027-717-7
JEL Classification Numbers:	E24, H2, J24, O33
Keywords:	Artificial intelligence, AI, technological change, labor market, fiscal policy, social protection systems, tax systems
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* Preparation of this SDN was led by Era Dabla-Norris and Ruud de Mooij. The authors thank Gita Gopinath and Vitor Gaspar for feedback and guidance and many IMF colleagues for useful comments. The views expressed herein are those of the authors and should not be attributed to the IMF, its Executive Board, or its management.

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Executive Summary

Rapid advances in generative artificial intelligence (gen AI) hold immense potential to transform production processes and significantly accelerate productivity growth. Gen AI has the power to revolutionize information availability and utilization, enabling governments to advance revenue mobilization and deliver more efficient public services across sectors, including health care, education, public procurement, and social transfers.

Alongside its promise, gen AI also presents challenges. A critical distinction between gen AI and past disruptive technologies (such as the steam engine, electricity, and early computers) lies in its potential for rapid diffusion. The sheer scale and speed of the transformation pose risks to labor markets. While automation and robots have already displaced low- and middle-skill jobs involving routine tasks, gen AI's capabilities extend to more intelligent automation, potentially amplifying job losses in cognitive occupations. Consequently, the labor income share in national income may further decline, exacerbating income and wealth inequality. Dominant firms in increasingly concentrated markets could reinforce their market power and enjoy monopoly rents.

This note provides analysis and guidance for policymakers as they prepare for the transformative impact of gen AI. *Special taxes on AI* to reduce the speed of AI investment are not recommended as they can be hard to operationalize and hamper productivity growth. That said, *corporate tax incentives* that currently encourage rapid labor displacement, prevalent in several advanced economies, should be reconsidered because they magnify the social costs of excessive labor market dislocation. At the same time, corporate tax distortions that hold up labor-saving investments, which are more prevalent in developing economies, can also be costly and especially harmful in less-disruptive labor market scenarios. General *taxes on capital income*, which have systematically declined across the world during past decades, should be strengthened to protect the tax base against a further decline in the labor-income share and to offset rising wealth inequality.

Fiscal policies can also cushion the negative labor market and distributional effects of gen AI and help distribute the gains more evenly. This calls for adequate *social protection systems* (social insurance, labor market programs, social assistance), as new analysis in this note shows. Most countries have scope to broaden the coverage and generosity of *unemployment insurance*, improve portability of entitlements, and consider forms of wage insurance. Combined with *active labor market policies,* this can help workers manage the transition while adapting to changing skill requirements. Innovative approaches that enhance digital technologies can facilitate expanded coverage of *social assistance* programs, particularly for those who suffer a prolonged impact from transitions or who work in the informal sector in emerging market and developing economies. *Education and training* policies must adapt to new realities, help prepare workers for the jobs of the future, and be better placed to offer lifelong learning. Sector-based training, apprenticeship, and upskilling and re-skilling programs could play a greater role in helping workers transition to new tasks and sectors.

Now that AI has matured to the commercial adoption phase, public funding should focus on areas less likely to receive private sector investment—such as fundamental research, necessary infrastructure (particularly in emerging market and developing economies), and applications in the public sector (education, health care, government administration).

Given uncertainty surrounding the transformative nature, impact, and pace of gen AI, policymakers must remain agile. Policy should bring about conditions that steer innovation and deployment in ways that harness the benefits of gen AI and serve collective human interests, and it should be ready to cushion the transition costs for workers and households and prevent rising inequality. Fiscal policies thus need to prepare for both businesses as usual and highly disruptive scenarios.

"It is coming inhumanely fast, and it will seem unbelievably unfair."
Richard Baldwin (2019)

Introduction

Rise of "cognitive" automation.[1] Artificial intelligence (AI) holds the potential to transform the nature of production processes and lift productivity and growth. Recent rapid advances in AI, particularly the advent of generative AI (gen AI) based on large language models that can produce new content, are greatly expanding the set of activities that can be performed more efficiently by computers than by humans. As a result, AI's potential applications in the workplace are broadening. Unlike past industrial transformations driven by general purpose technologies such as the steam engine, electricity, and early computers—gen AI can proliferate much faster than previous disruptive technologies. Even as businesses are working to figure out the best way to deploy the current generation of AI, advances are happening at breakneck speed, and the potential impacts are uncertain.

Untold benefits. Gen AI could revolutionize business and public sector operations. For firms and industries, it holds the potential for new revenue, cost savings, and improved products and processes. For governments, it portends improvements in public service delivery, making them more efficient and effective. For instance, fiscal operations, procurement, and revenue collection could benefit from enhanced fraud detection and automated audit and assurance processes. Personalized interactive learning, augmented reality, and remote patient monitoring could radically transform public education and health care, helping services reach people more quickly and equitably. Gen AI–fueled advances in public sector operations could subsequently inform more effective policy design and help transform regulatory operations.

Impact on labor markets and inequality. Adoption of gen AI will likely be uneven, and the size and rapid speed of transformation risk disrupting labor markets. Many jobs involving routine tasks have already been eliminated through laborsaving automation, which has driven down average wages and increasingly polarized wages and employment, even with the advent of new forms of work.[2] Evidence suggests that while earlier automation waves displaced mostly blue-collar (lower-skilled) workers, white-collar (high-skilled) workers are most exposed to AI.[3] But AI is also capable of powering more intelligent robots and could lead to further automation of blue-collar jobs. As such, laborsaving automation could amplify job losses in both low-skill and cognitive occupations, further reducing the labor share and wages relative to capital and exacerbating income and wealth inequality. Although AI could increase the productivity of firms and thus raise the demand for labor in nonautomated tasks—and generate new

[1] This note defines automation as technological advances that replace human labor with machine labor. Progress in AI may lead to greater automation, and the speed of this change may significantly increase after the advent of generative artificial intelligence (gen AI).

[2] Automation is hardly a novel phenomenon. Traditional sectors such as agriculture and manufacturing have already experienced large substitutions of labor with machine capital. Historically, jobs displaced by automation have been offset by the creation of new jobs, but computerization of white-collar services in many advanced economies has accelerated in recent years (Acemoglu and Restrepo 2018).

[3] Webb (2020) finds that AI is directed mainly at high-skill tasks and will affect highly educated and older workers. Felten, Raj, and Seamans (2023) obtain analogous findings when restricting their measure to machine learning applications more related to gen AI, such as language models and image generation. See also Eloundou and others (2023); Pizzinelli and others (2023); Autor (2024); and Brussevich, Dabla-Norris, and Khalid (forthcoming).

jobs—the transition could be costly. Gen AI could also reinforce the more unequal distribution of capital income seen in recent decades: rising market power and economic rents enjoyed by dominant firms in increasingly concentrated and winner-take-all markets (Kehrig and Vincent 2021; Acemoglu and Johnson 2023).

Alleviating costly transitions and broadening gains. Adequately distributing the gains and opportunities is necessary not just to protect the vulnerable and ensure social cohesion, but also to fully harness the opportunities presented by gen AI. By offering financial support during unemployment, promoting new skills acquisition, and creating a safety net, social protection systems can help individuals adapt to job market changes. Traditionally, social protection systems have encompassed payroll-based insurance components (for example, unemployment benefits), lifelong education and training initiatives, and cash transfers and other forms of noncontributory social assistance programs. These all provide financial support to low-income households during long periods of unemployment. A largely unexplored question is whether and how social policies will have to be reimagined in the face of disruptive technological changes from AI.

Taxation of investment in AI: a growing debate. Should investment in AI be taxed? Taxation, alongside regulation, can mitigate the disruptive labor market implications of rapid job displacements by discouraging and slowing the deployment of automation. The downside of such taxes is, however, that they distort productivity-enhancing investment and reduce economic growth. While the net balance for social welfare is unclear and may vary between scenarios, an important question is how such a tax could be implemented in practice.

Increasing importance of taxing capital income. Gen AI, like other types of innovation, can lead to higher top-income inequality. A long-held view is that progressive income taxes can help address rising inequality, including through the taxation of capital income, while balancing the trade-off with efficiency. Also, higher investment in education and social spending to broaden the gains from AI require higher public revenue, while labor substitution can do the opposite if capital income is taxed less than labor income. Developing economies specializing in labor-intensive sectors and exposed to “reshoring” are particularly at risk of losing tax revenue (Korinek, Schindler, and Stiglitz 2022).

Steering innovation in AI. Fiscal policies may also influence the path of innovation and deployment of AI. Some have argued that policies could also favor applications that expand, rather than substitute for, human capabilities and could lead to new occupational tasks (Acemoglu, Autor, and Johnson 2023). While it is unclear what this entails in practice, development opportunities in emerging markets from AI deployment could be significant.

This note. This note focuses on the role of fiscal policies in supporting a more equal distribution of gains and opportunities from gen AI. A key question is how countries can use spending policies and reform tax systems to mitigate labor disruptions during the transition and offset adverse distributional impacts of innovation while preserving AI-driven productivity growth. Specifically, the note addresses the following four questions:

- How have social protection systems helped reduce labor market disruption during past episodes of automation?
- Looking ahead, how can countries strengthen social spending during rapid technological transitions?
- Have tax systems provided excessive incentives for automation? Should automation be taxed to mitigate labor market disruptions and pay for its effects on workers?
- How should governments design redistributive taxation in the face of inequality and winner-take-all dynamics from gen AI—especially taxes on capital income?

Previous work and contribution to literature. Recent studies have focused on the productivity and labor market impacts of AI (Korinek, Schindler, and Stiglitz 2022; Korinek 2023a; Baily, Brynjolfsson, and Korinek 2023; Brynjolfsson, Li, and Raymond 2023; Noy and Zhang 2023; Cazzaniga and others 2024).[4] Fiscal policies aimed at spreading the gains and mitigating the risks from AI are less well studied. This note builds on some pioneering studies in this field, including Berg and others (2021); Beraja and Zorzi (2024); Costinot and Werning (2023); Guerreiro, Rebelo, and Teles (2022); and Thuemmel (2023). Our contributions focus on social protection and tax policies. In particular, this note offers new empirical analysis of the role of social protection systems during past automation waves and discusses the desirable characteristics of social spending in the face of disruptive technological developments. Model simulations illustrate the impact of spending and tax policies on labor market outcomes and welfare. The note also presents a novel discussion of how current tax systems affect firms' decisions to invest in labor-displacing capital assets, examines the case for taxing AI, and elaborates on recommendations to enhance the taxation of capital income. Finally, the note briefly touches on whether fiscal policies should promote innovation and deployment of gen AI.

Caveats. How gen AI technologies will evolve and transform economies is highly uncertain. Different scenarios are plausible regarding (1) the speed of improvement in the capabilities of AI, (2) the degree of adoption of the newest technologies across countries and firms and how they will be used, (3) the extent to which AI will replace or complement different types of workers, (4) how people will adapt to the new realities of work, (5) the policy responses of governments, and (6) the implications of these factors for productivity growth and economic well-being. Fiscal policies must adapt to changing conditions and prepare for both business as usual and highly disruptive scenarios.

[4] See also Aghion and others (2022), Autor (2022), and Comunale and Manera (2024) for comprehensive literature reviews.

Upgrading Social Protection Systems

Alleviating labor market disruptions. How can social protection systems deliver stable employment and productivity growth (efficiency) while providing adequate protection to workers (equity) in a world with gen AI? *Social insurance*, such as unemployment insurance (UI), can enhance individual and social welfare by smoothing consumption in the presence of credit and insurance market failures. It enables the unemployed to look for better jobs that match their skills, thereby improving the quality of job matches (Marimon and Zilibotti 1999; Chetty 2008). Active labor market policies (ALMPs) complement UI and can shorten periods of unemployment (unemployment "spells") by improving workers' skills (through retraining programs) and reducing information gaps between job seekers and job providers. *Social assistance* programs, such as cash transfers, provide financial support to low-income households during long unemployment spells. This section looks at the role of UI, ALMPs, and social assistance programs in alleviating adverse labor market outcomes in the past and assesses whether these are fit for purpose in the future. Although gen AI has broader implications for high-skilled workers in cognitive tasks, lessons from previous waves of automation offer valuable insight into how social protection systems can help cushion the negative impact on labor markets.

Lessons from Past Automation Waves

Labor force displacement from automation. The impact of automation on labor markets depends on whether the technology is substitutable for or complementary to various types of tasks performed by workers. Mounting evidence indicates that automation in recent decades displaced workers in routine tasks, pushing down average wages and intensifying job polarization. Increased use of industrial robots in the United States hurt local labor markets. It drove down employment and wages, especially for manual and routine jobs (Acemoglu and Restrepo 2020; Restrepo 2023), with displaced workers moving into lower-paying occupations (Braxton and Taska 2023). Displacement of lower-skilled workers is also observed in Europe (for example, Graetz and Michaels 2018; Acemoglu, Lelarge, and Restrepo 2020), although workers adapted over time. Dauth and others (2021) find that lost manufacturing jobs in Germany were replaced by new positions in the service sector, and young workers adjusted their education choices, favoring college and university over vocational training.

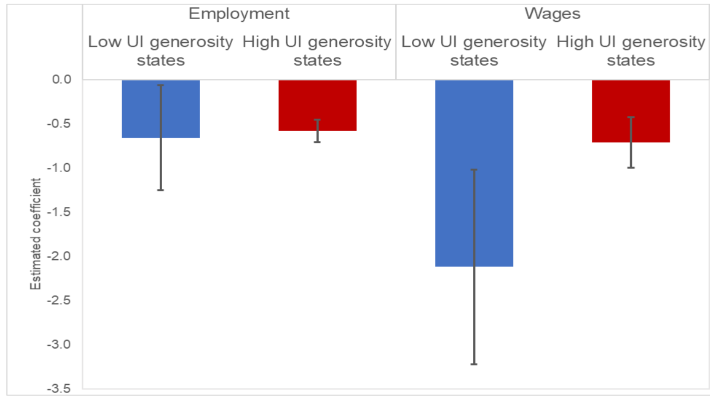
Conceptual approach. Did social protection programs reduce the negative impact of automation on labor market outcomes? To answer this question, the analysis that follows provides new evidence on how social protection can mitigate the long-term effects of industrial robots on employment and wages at the level of commuting zones in the United States. As in Acemoglu and Restrepo (2020), the underlying intuition is that increased robotization in a commuting zone can reduce employment and wages relative to other commuting zones. This reflects both the direct effects of robot adoption on employment and wages and the spillover effects on the nontradables (service) sector resulting from the decline in local demand.[5] The novel analysis then exploits differences in the generosity of unemployment insurance and social

[5] Specifically, exposure to robots is an adjusted Bartik-type measure that combines industry-level variation in the use of robots and industry employment shares at the commuting zone level, adjusting for overall expansion of each industry's output.

assistance across states to examine whether these programs helped attenuate the adverse labor market outcomes (see Brollo 2024 for details).

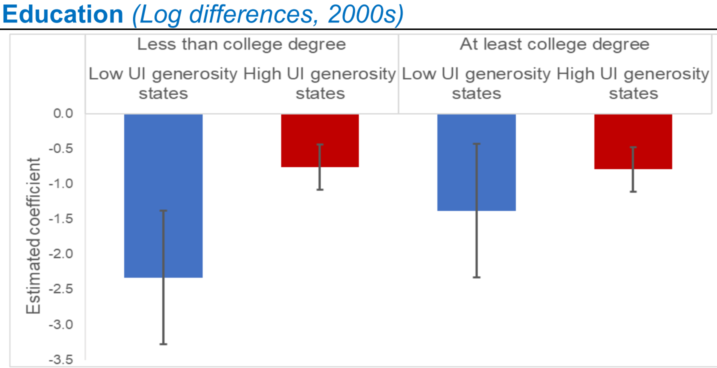
Cushioning effect of unemployment insurance. The empirical results reported in Figure 1 indicate that the impact of robotization on employment does not depend on UI generosity. This is not surprising: UI benefits are temporary and thus unlikely to generate long-term effects (neither positive income effects that boost local labor demand nor negative effects on labor supply because workers are discouraged from job search). In contrast, states with more generous UI benefits saw a smaller decline in wages as a result of robotization—about two-thirds smaller than other states. This finding suggests that more generous UI allows displaced workers to find jobs that better match their skills, which contributes to more efficient labor allocation. This effect is particularly pronounced for workers without a college degree (Figure 2), possibly because these workers rely relatively more on unemployment insurance benefits when unemployed. These findings suggest that UI programs can effectively lessen the adverse effects of industrial robots on wages because they facilitate intensive job search and allow more time for new skills acquisition, potentially leading to better job matching and increased worker productivity.

Figure 1. Effect of Robots on Employment and Wages in the US Local Labor Market: The Role of Unemployment Insurance *(Log differences, 2000s)*



Source: Acemoglu and Restrepo (2020) and IMF staff calculations.
Note: The figure presents estimates from instrumental variable regressions of employment and wages on robot adoption using cross-sectional data on US commuting zones. The dependent variables are change in employment to population ratio or change in log of average hourly wage in a commuting zone over the sample period 2000–07. Right side variables include (1) a measure of exposure to robots, which combines industry-level variation in the use of robots and baseline employment shares at the commuting zone level, adjusting for overall expansion of each industry's output; (2) a dummy variable capturing high (low) unemployment insurance (UI) generosity, which is equal to one if UI generosity is above (below) the median across US states; (3) the interaction between (1) and (2). Regressions also include controls for commuting zone demographic characteristics, the share of employment in manufacturing, exposure to Chinese imports, and the share of employment in routine jobs. The bars show the effect of robot adoption for commuting zones in states with high and low UI generosity, separately. The generosity of UI benefits at the state level is measured as the product of the maximum legal benefit amount and its duration. Whiskers indicate 95 percent confidence intervals. Differences between high and low UI states are statistically significant at the 1 percent level. See Brollo (2024) for details.

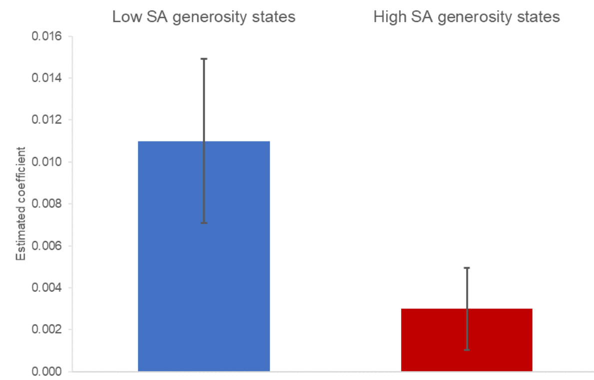
Figure 2. Effect of Robots on Wages in the US Local Labor Market: The Role of Unemployment Insurance by Levels of Education *(Log differences, 2000s)*



Source: Acemoglu and Restrepo (2020) and IMF staff calculations.
Note: The figure presents estimates from instrumental variable regressions of wages for workers with different educational attainment on robot adoption using cross-sectional data on US commuting zones. See the Figure 1 note for regression specification. Differences between high and low UI states for workers with less than a college degree are statistically significant at the 1 percent level. See Brollo (2024) for details.

Impact on poverty. In addition to its effects on labor markets, robotization may also contribute to increasing poverty, especially if the negative impact of robotization is more pronounced for workers at the bottom of the wage distribution. These workers are at higher risk of falling into poverty, because it is harder for them to find new jobs with similar pay. Social assistance programs can play a key attenuating role in this regard. Overall, the analysis shows that robotization resulted in a small long-term increase in poverty: one additional robot per thousand workers increased the poverty rate by 0.3 percentage point (3 percent increase). However, most of the increase in poverty as a result of robotization is attenuated in commuting zones where social assistance is relatively more generous (Figure 3).[6]

Figure 3. Effect of Robots on Poverty: The Role of Social Assistance *(Log differences, 2000s)*



Source: Acemoglu and Restrepo (2020) and IMF staff calculations.
Note: The figure presents estimates from instrumental variable regressions of the poverty rate on robot adoption. The dependent variables are the change in the poverty ratio in a commuting zone over the sample period 2000–07. Right side variables are the same as noted in Figure 1. Whiskers indicate 95 percent confidence intervals. Differences between high and low SA states are statistically significant at the 1 percent level. See Brollo (2024) for details. SA = social assistance.

Lessons from the past. Overall, these findings suggest that the design of social protection systems played a role in ameliorating adverse labor market and poverty impacts in the past. Although robotization can lead to displacement of workers in routine and manual tasks, the impact of gen AI could potentially be more widespread, replacing a broader spectrum of both routine and high-skill nonroutine tasks. This calls for more fundamental changes in education and training systems and policy frameworks to mitigate potential broader societal implications. The extent to which existing systems will need to be upgraded in a world of rapid technological change and potentially more significant labor market displacement is discussed in the next section.

Strengthening Social Spending during Rapid Technological Transitions

Costly transitions from disruptive technological advances. AI could generate significant long-term productivity and growth dividends, but the transition may be very costly owing to labor market mismatches and long periods of unemployment as a result of skill specificity. For instance, labor market adjustment can be slower if gen AI benefits mainly production activities requiring specific skills that differ from those used in the rest of the economy (Adão, Beraja, and Pandalai-Nayar 2024).[7] Workers may also face barriers to mobility and go through long unemployment or retraining spells before finding a new job. Indeed, technology-induced labor displacement often proceeds over a generation, with older workers

[6] The generosity of social assistance at the state level is based on the generosity of Temporary Assistance for Needy Families (TANF) benefits, the largest cash assistance program in the US. The generosity of TANF benefits in each state is measured by the maximum monthly benefit for a family of three with no income in 1999, the year before the period covered in the analysis.

[7] Adão, Beraja, and Pandalai-Nayar (2024) show that when skill specificity is stronger, as in the case of information and communication technology (ICT), adjustment of labor markets is driven more by the gradual entry of younger generations than by reallocation of older incumbent workers.

leaving the workforce and fewer younger workers entering such jobs (Bürgisser 2023). The advent of AI could aggravate adjustment costs if it entails broader substitution of nonroutine tasks (Acemoglu 2021) and affects younger workers for whom early retirement is not an option. This section sheds light on pertinent design features of UI, and how UI and ALMPs could be optimally combined to address potential labor market disruptions from gen AI.

Model-based analysis and relevant channels. A model-based analysis is used to identify optimal characteristics of social spending policy in response to disruptive technological advances (see Annex 1 for details). The analysis extends a tractable HANK-DGSE model with labor market frictions developed by Ravn and Sterk (2021). The model features a potential for automation and two sectors of production, allowing for a discussion of the asymmetric sectoral impacts (see also McKinsey 2023) and policies supporting sectoral mobility. Each sector employs labor, traditional capital, and automated capital that can substitute for labor, following the approach of Berg, Buffie, and Zanna (2018). Matching workers and firms is costly (for example, as a result of search and matching frictions). Unemployed workers can search for jobs in both sectors, but changing sectors means a period of unemployment, which can be lengthy if there is skill mismatch. The model features UI support and ALMPs designed to facilitate sectoral mobility. The expenses associated with these policies are funded with labor income taxes, ensuring budget neutrality each period. Taxes on automated capital are considered in the next section.

Accounting for trade-offs and costly transitions. To understand gen AI's potential impact on income, productivity, and labor markets, the model simulates a sizable acceleration in the productivity of automated capital in one sector. The baseline scenario is calibrated to a representative advanced economy and assumes no policy changes. The increase in automation results in a gradual reduction in labor demand in the sector, leading to a 20 percent decline in employment in the new steady state (approached in about 15 years).[8] At the same time, the new steady state is characterized by an increase in wages of about 15 percent, as automation increases aggregate productivity (Figure 4).[9] The long-term effects of AI are subject to high uncertainty. For instance, Korinek (2023b) and Korinek and Suh (2024) show that output could double in 15 years with a gradual advance in AI. Cazzaniga and others (2024) find a smaller increase of 10–16 percent, and Acemoglu (2024) suggests even smaller gains, with an increase in GDP of about 1–2 percent over the subsequent 10 years.[10] Irrespective of the magnitude of potential long-term benefits, the transition entails short-term costs. Unemployment rises temporarily because of the cost of relocating workers across sectors, which reduces the number of job vacancies posted by firms. Furthermore, unemployment hurts the most vulnerable groups, with a substantial fall in consumption of

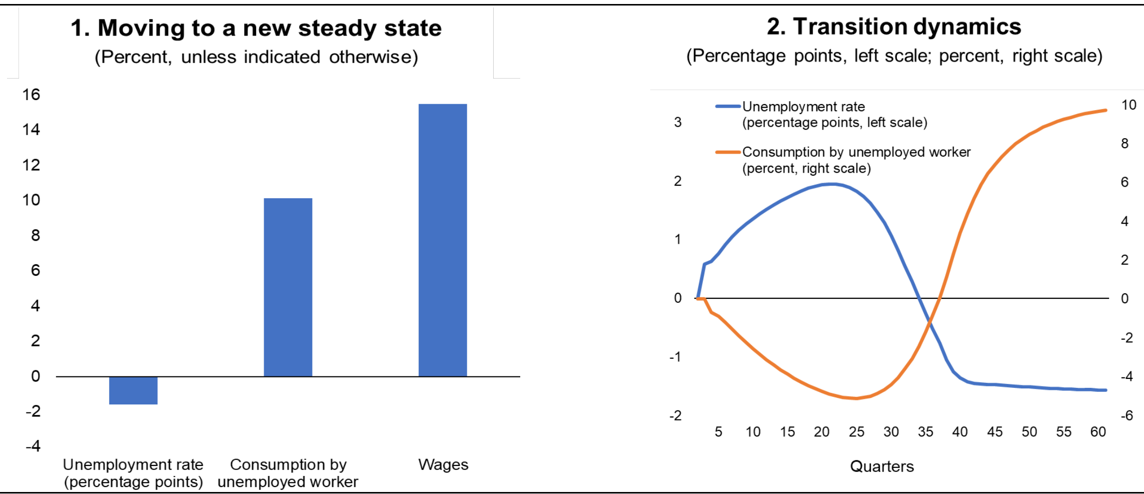
[8] This simulation is based on a projection by McKinsey (2023) that automation could replace the time spent on work activities by 20 to 30 percent by 2030. Note however that the projection includes both the extensive and intensive margins, whereas the model captures only the extensive margin.

[9] The unemployment rate decreases in the new steady state, primarily because of the rise in labor demand in the sector that is not affected by automation. This increase in demand more than compensates for the job losses in the sector that faces automation shocks, as a result of complementarity between sectors in producing the final products. Over the long term, wages also increase, which, in turn, increases unemployment benefits as a proportion of these wages. Consequently, this enhancement in support improves the consumption levels of unemployed workers relative to their initial consumption figures.

[10] Cazzaniga and others (2024) assume that the AI shocks would reduce the labor share by 5.5 percentage points based on the historical change observed in the United Kingdom between 1980 and 2014. Annex Figure 1.1 shows that assuming a similar size of the shock in our model leads to a similar increase in output.

unemployed workers.[11] Incomplete insurance gives rise to a precautionary saving motive that further propagates and amplifies aggregate shocks (Ravn and Sterk 2021). Such transition costs highlight the need for policies to support affected workers and households.

Figure 4. Baseline Automation Shocks



Source: IMF staff calculations.
Note: The figure presents the baseline automation scenario without policies, with changes between the initial and final steady states in panel 1 and deviations from the initial steady state over time in panel 2. The model is calibrated to a representative advanced economy. See Annex 1 for details. ppts = percentage points.

Balancing UI benefit adequacy and work incentives. By providing income insurance for unemployed workers, UI can help cushion the consumption loss and mitigate the adverse effects of higher unemployment. This is particularly important in the case of unemployment driven by technological transformation, when workers need more time to re-skill and search for jobs in other sectors, which suggests a need for relatively longer duration of unemployment benefits. Two illustrative designs of UI are considered: (1) a permanent increase in the UI replacement ratio by 1 percentage point; and (2) a temporary asymmetric adjustment rule that increases the replacement ratio in proportion to the previous quarter's unemployment gap by a factor of 0.6 once the unemployment rate rises by more than 1 percentage point relative to its steady-state level (Figure 5). Both options effectively mitigate the drop in consumption by unemployed workers compared with the baseline. Nevertheless, a permanent increase in UI could discourage job searches and lead to an increase in the unemployment rate (Blanchard and Tirole 2008), thereby lowering overall welfare.[12] In addition, higher unemployment and benefit generosity can be fiscally costly, especially if AI destroys higher-wage jobs, requiring distortive tax hikes or public debt accumulation that further weigh on economic activity. Conversely, scaling up unemployment generosity during the transition could help manage fiscal costs and mitigate negative job search incentives while still providing sufficient income support—along the lines of the evidence presented in the

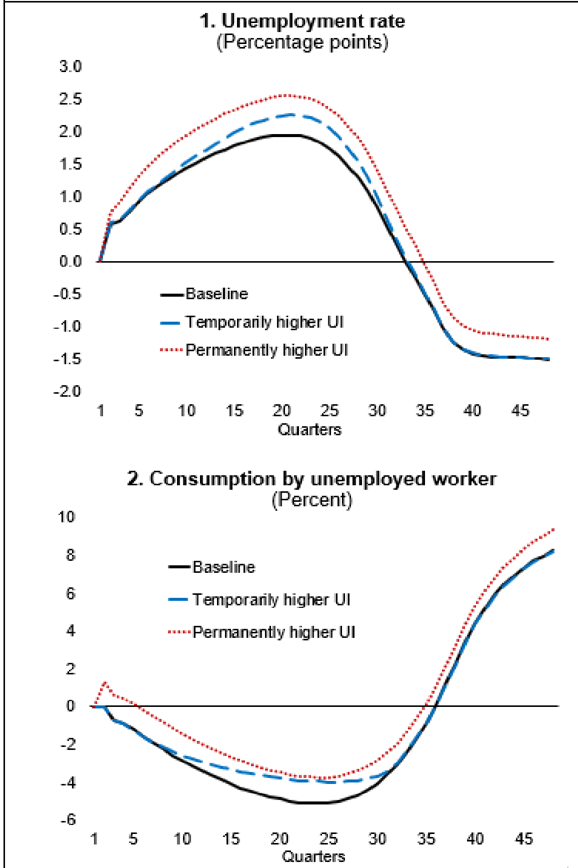
[11] In the model, the only source of income for unemployed workers is unemployment income support. The consumption fall would be mitigated to the extent affected workers are wealthier and hold larger liquid savings to smooth consumption. Yet liquid wealth is very low for many households in the United States (Challe and others 2017).

[12] A smaller permanent increase in the replacement ratio would mitigate the job search disincentive, but at the cost of smaller consumption smoothing by the unemployed.

previous section. Comparing the two schemes, the temporary UI adjustment aligned with unemployment levels appears to yield the highest welfare benefits. Overall, UI will need to be carefully designed to facilitate mobility and adjustment while minimizing the adverse effect on efficiency, but its efficacy will also depend on how quickly advances in AI materialize and associated transition costs. For instance, if advances in AI accelerate even further in coming years and all cognitive work can be performed by machines over a relatively short period, disruption to the workforce would be the most severe. Preparing for such a scenario will require rethinking the design of unemployment insurance programs; for example, specifying benefits that depend on the duration of unemployment spells and linking them better with training and re-skilling programs.

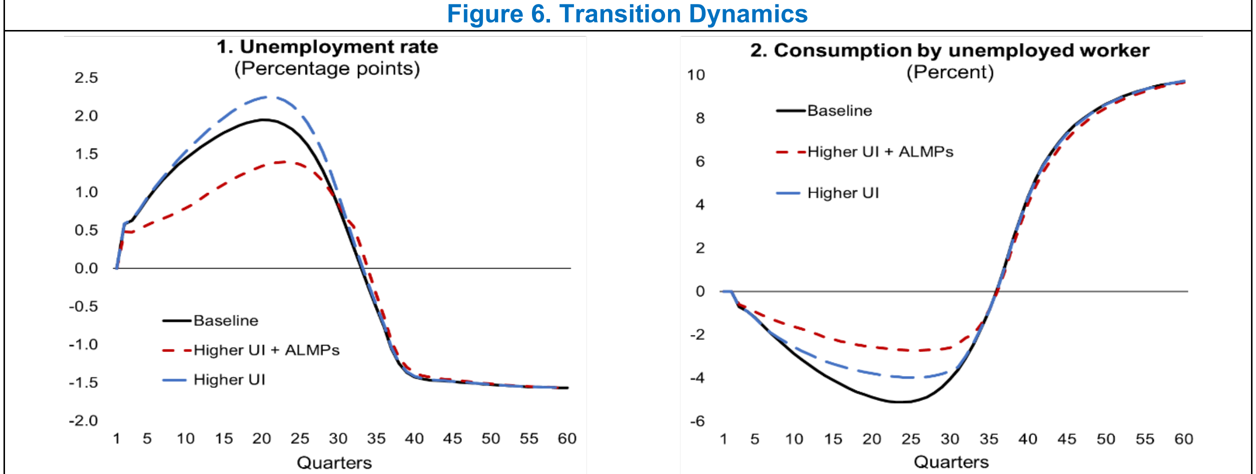
Combining UI and ALMPs. ALMPs in the form of training and skill development programs can enhance the employability of workers and improve the quality of matching between workers and employers, particularly in response to asymmetric shocks affecting specific skill sets. An adequate mix of income and employment support can effectively mitigate the surge in unemployment, consequently helping to limit the fall in wages (Figure 6). As a result, combining UI and ALMPs can help reduce

Figure 5. Different UI Programs



Source: IMF staff calculations.
Note: The figure shows the baseline simulation and two unemployment income support programs: a permanent increase in the replacement rate of 1 percentage point and a temporary program aligned with the state of the economy. These policies are funded with labor income taxes, ensuring budget neutrality each period.

Figure 6. Transition Dynamics

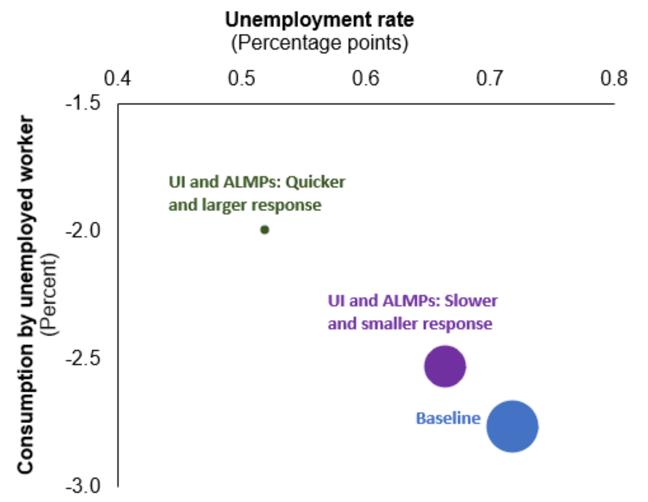


Source: IMF staff calculations.
Note: The figure presents the baseline scenario and two policy options: temporary unemployment income support (UI) and a combination of UI and active labor market policies (ALMPs). These policies are funded with labor income taxes, ensuring budget neutrality each period.

the transition costs while at the same time accelerating labor reallocation. As before, the policy mix and its efficacy in ameliorating labor market impacts will depend on the pace of automation and size of transition costs. For instance, the value of social protection could be smaller if gen AI displaces older, skilled workers with larger savings. Similarly, skill specificities will imply different types of ALMPs than have been considered in the past and could require broader access to effective training programs.

Distinct challenges facing emerging market and developing economies. While most studies on AI exposure focus on advanced economies, some evidence suggests that emerging market and developing economies have a lower share of high-skill occupations and, therefore, are less exposed to AI (Pizzinelli and others 2023). Nevertheless, emerging market and developing economies, on average, are also less prepared to adopt AI (Cazzaniga and others 2024). For instance, labor market policies and social protection systems in many emerging market and developing economies are more limited in scope and scale because of their large informal sectors, budgetary constraints, and less-developed institutional capacity. Furthermore, these economies have a larger share of young people who are *not* in employment, education, or training (ILO 2022), which raises concern about their ability to adjust to technological transitions (Adão, Beraja, and Pandalai-Nayar 2024). At the same time, larger insurance and credit market imperfections and less personal wealth available for consumption smoothing imply that the welfare gains from UI are potentially greater than in advanced economies (Chetty and Looney 2006).[13] A model-based illustration (Figure 7) suggests that countries with more fiscal space and capacity to effectively scale up income support and ALMPs can significantly mitigate the impacts of the shock and more quickly realize the higher productivity benefits.

Figure 7. Illustrative Scenarios for Emerging Market and Developing Economies

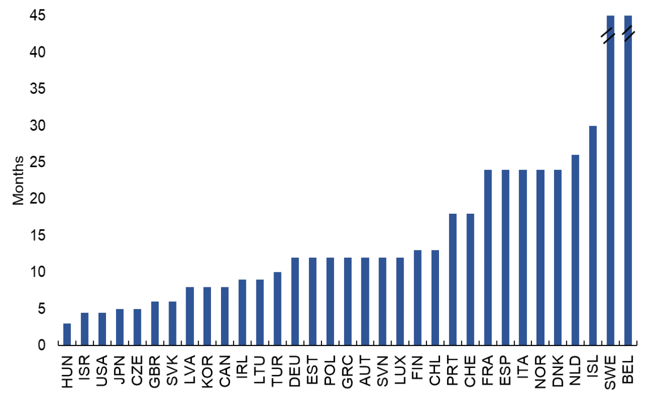


Source: IMF staff simulation.
Note: The figure presents the baseline scenario and two policy scenarios. Reflecting the narratives discussed in the text, the exposure of emerging market and developing economies to automation shocks is calibrated smaller and more gradual than for the advanced economy counterparts, but their policy space is more constrained. Both policy scenarios include unemployment insurance and active labor market policies (ALMPs), but one features a larger response and faster deployment (2.5 years after the initial shock), while the other is smaller, with delayed implementation of ALMPs (five years after the initial shock). The values of the unemployment rate and consumption change are averaged over 60 quarters. Bubble size is proportional to the amount of time the unemployment rate is 1 percentage point above its initial steady state.

[13] For emerging market and developing economies with large informal sectors, providing income support and facilitating the transition by training or retraining also help prevent workers from dropping out of the formal sector in response to automation disruptions.

Upgrading unemployment insurance systems. The extent to which UI systems cushion the negative effects of AI will likely depend on the exposure to automation and coverage, generosity, and design features. Many advanced economies have established generous unemployment benefit programs, but the extent to which workers are eligible for such programs varies. In addition, the maximum benefit duration is usually less than 12 months (Figure 8), and the support declines over the unemployment spell.[14] Access to basic UI is not universal but largely fragmented along occupational lines, and benefits are not portable. Minimum contribution durations typically exclude temporary workers and labor market (re-) entrants, and maximum benefit receipt durations exclude the long-term unemployed in most countries. Policymakers could consider extending the scope, portability, and flexibility of unemployment insurance to allow sufficient time to allow for retraining. There is also a growing debate over wage insurance that entails a temporary subsidy for displaced workers who find reemployment at a lower wage, which would shorten the duration of unemployment and support workers for whom job training may be less effective (Hyman and others 2021).[15]

Figure 8. Maximum Benefit Duration



Source: OECD (2023b). Sign "//" indicates a duration of more than 45 months.
Note: Data labels in the figure use International Organization for Standardization (ISO) country codes.

Enhancing social assistance. Social assistance, which contributes to equity in societies, could be strengthened by adopting comprehensive programs that support workers directly or indirectly affected by technological shifts, such as those facing long-term unemployment or reduced local labor demand as a result of industry closures or automation. At one end of the spectrum are enhanced means-tested guaranteed minimum income programs—which distribute cash or other assistance to households, with benefits gradually declining as income rises—with other forms of support (for example, systematically investing in training and job transition services, as discussed later). At the other end is providing unconditional benefits to all, independent of income or employment status. The latter approach, by design, would cover higher-income groups likely to be hurt by AI, potentially generating significant fiscal costs (IMF 2017b). Such an approach may not be desirable at this point since the negative effects on labor markets are not widespread and existing social safety nets offer more protection at lower cost in most advanced economies. That said, the appropriate design, coverage, and eligibility of social assistance programs must be carefully assessed in the face of potentially widespread disruptive technological changes.

[14] The maximum US benefit duration is on the low side of Organisation for Economic Co-operation and Development countries: most states provide a maximum of 26 weeks.
[15] As part of the broader Trade Adjustment Assistance in the United States, there is a wage insurance program in place for workers ages 50 and older in particular industries that are severely affected by import competition (Frey 2019).

Strengthening social protection in emerging market and developing economies. While almost half of unemployed workers receive unemployment benefits in advanced economies, unemployment income support programs in most emerging market and developing economies cover only a very limited number of people, which reflects large informal sectors and limited administrative capacity. As a result, in most emerging market and developing economies, income support to the unemployed is provided mostly through social assistance programs (Brollo and others 2024a). Innovative approaches relying on digital technologies can enable rapid expansion of coverage, but this can involve important trade-offs between achieving high coverage and containing the associated fiscal cost (Brollo and others 2024b).

Upskilling and training workers. To facilitate transitions for those already in the labor force, some countries have taken steps to promote preemptive acquisition of new skills ("lifelong learning") while overcoming credit constraints. For example, Singapore offers unconditional grants to all adults for training throughout their working lives. Less stable employment relationships in the future also put a premium on educational and training opportunities centered on workers rather than jobs. Finally, employer-provided training may need replacement or substitution by other programs, with implications for ALMPs. Evidence suggests that sector-based training programs in the United States that focused on workers in particular industries (for example, manufacturing, health care, transportation, ICT) led to earnings gains of 14–38 percent in the year following training completion (Katz and others 2022), with persistent gains. Other studies have found that upskilling can be more beneficial than on-the-job training programs in the case of workers displaced by "offshoring" (Humlum, Munch, and Rasmussen 2023). These findings shed light on the nature of policies needed in the face of job loss or downsizing as a result of AI and automation. Looking ahead, the viability of re-skilling and retraining programs as opposed to alternatives such as early retirement should be assessed to consider the challenges older workers might face in adapting to new technologies.

Upgrading infrastructure for social assistance systems. To effectively provide sufficient coverage and benefits, social assistance programs in both advanced and emerging market and developing economies will require robust and universal information systems for beneficiary identification and verification. These systems must be integrated across various social protection programs and must have efficient delivery systems and strong institutional frameworks. To foster beneficiaries' prospects of finding productive employment, ALMPs must be integrated with social assistance programs for which, for example, continued eligibility for benefits is conditional on participation in programs that offer job search support and counseling services or skills training (IMF 2022).

Upgrading Tax Systems

AI and taxation. Whereas the previous section shows how social protection systems can cushion the distributional and labor market implications of gen AI, this section first explores the extent to which current tax systems already direct investment allocations toward or away from AI—for example, through capital allowances and incentives. Building on recent literature that explores the role of taxation on robots and other labor-saving and skill-biased technological change, it then analyzes the potential role of special taxes on gen AI. Finally, the redistributive role of taxation in the context of gen AI—notably the taxation of capital income—is discussed. This is especially important to the extent that gen AI exacerbates the concentration of wealth as a result of economic rents from rising market power. Moreover, if gen AI reduces the labor income share and capital income is taxed less, requisite tax revenue will fall even as countries must pay for upgrades to social protection systems.

Do Current Tax Systems Favor Labor-Displacing Investments?

Existing tax systems already differentiate between investment in broad asset categories. These categories might include equipment (for example, machinery and computers), structures (for example, offices), inventory, and intellectual property (for example, software, patents). Different tax treatments for these asset categories result from deliberate policies, such as accelerated tax depreciation, investment tax credits, and reduced tax rates for particular assets (for example, intellectual property). The incentive to invest in a particular asset as provided by the tax system can be summarized by the marginal effective tax rate (METR), which measures the extent to which taxation increases the pretax rate of return needed by investors to break even (the cost of capital). A neutral tax system equalizes METRs across assets, while variations in METRs reflect incentives and disincentives for private investment. For example, a higher METR for machinery, relative to buildings, discourages investment in machinery while favoring that in buildings. Investments in machinery and equipment (including tangible ICT) are often incentivized because they are deemed to have a higher social return and stronger impact on economic growth.[16] Further, investments in research and development and intellectual property are often incentivized to internalize positive externalities from innovation. However, differential taxation can also inadvertently result in misallocation of capital assets and reduce productivity (IMF 2017a; Fatica 2017; Liu 2011).

Complementarity with labor. Variations in METRs can provide incentives for investments in labor-displacing versus labor-augmenting technologies. Indeed, different asset categories vary in their complementarity with labor. For example, investments in nonresidential structures enhance the productivity of labor, whereas certain forms of purchased software and patents are likely to be labor saving—although the degree of complementarity with labor may differ vastly within asset classes. Evidence for advanced economies suggests the following:

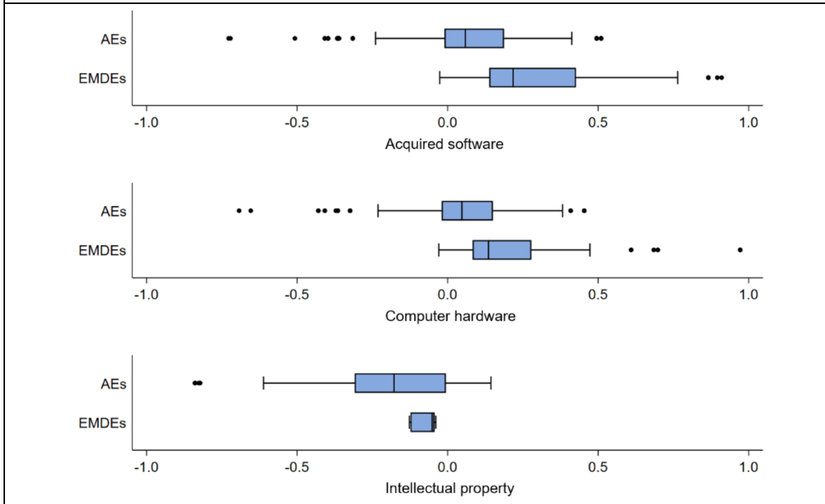
- Machinery and equipment tend to be labor complements (Aum and Shin 2022; Jerbashian 2022).
- Computer hardware complements high-skilled labor but substitutes for low-skilled labor (Berman, Bound, and Griliches 1994; Berndt and Morrison 1995; Autor, Katz, and Krueger 1998).
- Software is generally found to replace labor, with an estimated elasticity of substitution of 1.7 (Aum and Shin 2022). Acquired intellectual property represents a broader asset category that could have similarly high substitution elasticities; for example, in the case of firm-specific gen AI tools. However, gen AI may encompass both labor-saving and labor-complementing assets, such as purchased software for AI algorithm development and robust data infrastructure, high-performance computing hardware, and acquired intellectual property, as well as investment in AI researchers and employee

[16] For example, see Ohrn (2019), Zwick and Mahon (2017), and House and Shapiro (2008) for recent evidence in the United States; Schaller (2006) for Canada; and Maffini, Xing, and Devereux (2019) and Bond and Xing (2015) for Europe, among others.

training programs.

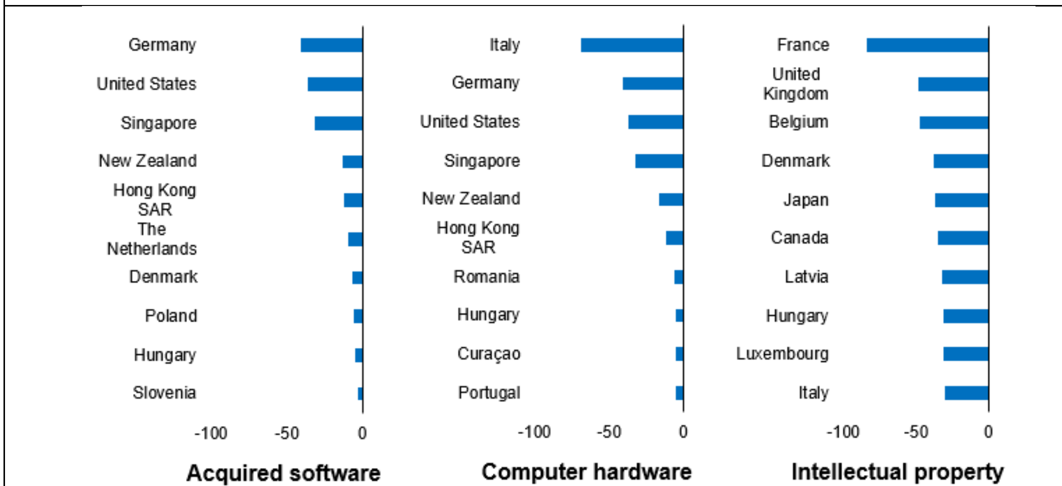
Some tax systems currently favor labor-displacing investments. Tax-induced (dis)incentives for investment in software, computer hardware, and intellectual property can be measured by their respective METRs in comparison to that for buildings, for example (a positive difference indicating a higher tax and thus a disincentive for these investments). Figure 9 shows that the tax advantage for intellectual property (that is, acquired patents, utility models, trademarks) is almost universal across countries, probably to capture positive spillovers from innovation. However, most economies impose a higher tax on acquired software and computer hardware than on buildings. Yet there is significant heterogeneity across economies. For instance, the tax systems of Germany, the United States, The Netherlands, New Zealand, Singapore, and Hong Kong SAR tend to favor acquired software and computer hardware (Figure 10) and thus encourage automation. This can be undesirable, especially in a disruptive AI scenario. Most other countries, especially developing economies, discourage investment in these labor-saving assets (see Annex Figure 2.2). This can also be

Figure 9. Corporate Tax Biases for Labor-Saving Assets
(Percent)



Sources: OECD 2023d; and IMF staff calculations.
Note: The figure shows the extent of corporate tax biases for labor-saving assets, measured as the METR for acquired software and computer hardware relative to the METR for buildings in 2017–22; the METR for intellectual property is measured relative to the METR for buildings in 2017–20. A positive value denotes a higher tax burden on the asset relative to buildings. METRs are based on the assumption that the investment is financed by equity. AEs = advanced economies; EMDEs = emerging market and developing economies; METR = marginal effective tax rate.

Figure 10. Corporate Tax Bias for Labor-Saving Assets by Economy: Top 10
(Percent)

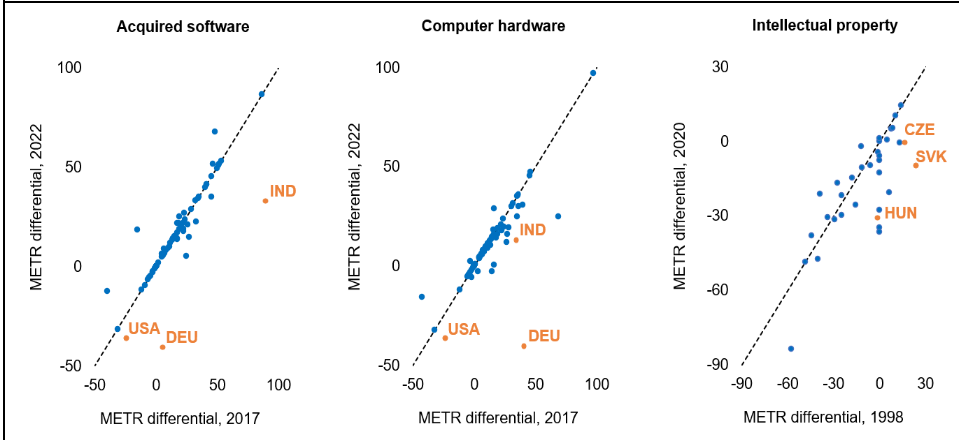


Sources: OECD 2023d; ZEW 2021; and IMF staff calculations.
Note: The figure shows the 10 economies with the largest corporate tax bias favoring labor-saving assets. The bias is measured as the METR for each asset type relative to the METR for buildings and is based on a sample of 85 economies for 2022 for acquired software and computer hardware; for intellectual property the sample covers only the EU-27 for 2020. A negative value denotes a lower METR on the asset relative to buildings. METR = marginal effective tax rate.

distortive, especially in a scenario with more modest labor market implications, and could stymie AI deployment.

Changes over time. Some countries have scaled up tax incentives to invest in labor-saving assets over time (Figure 11). For example, the US Tax Cuts and Jobs Act (TCJA) became effective in 2018, allowing companies to fully expense capital expenditures on acquired software and computer hardware.[17] Germany implemented a similar approach in 2021, and India reduced its statutory corporate income tax (CIT) rate in 2020. which disproportionately increased the value of tax depreciation for acquired software and computer hardware. Hungary, the Slovak Republic, and the Czech Republic introduced accelerated tax depreciation for acquired intellectual property assets in the early 2000s.[18] For the median country, the tax treatment of software and hardware became more generous by about 0.8 and 3 percentage points (relative to buildings) over the years 2017–22.[19] These reforms may have incentivized automation.

Figure 11. Changing Corporate Tax Bias



Source: IMF staff calculations based on ZEW 2021 and OECD 2023 data.
Note: The figure plots the METR differentials for investments in intellectual property in 1998 against those in 2020, such that the diagonal corresponds to the case where the tax treatment relative to nonresidential structures has not changed over time. METR differentials for acquired software and computer hardware compare 2017 to 2022. Data labels in the figure use International Organization for Standardization (ISO) country codes.

Should AI Be Taxed?

Taxing automation. The implications of automation for labor markets and income inequality have sparked debate over whether such investments should be taxed—for example, through a robot tax. This subsection reviews these arguments and discusses the case for taxing AI.

Argument for not taxing AI: production efficiency. A natural starting point for the analysis of AI and taxation is the principle that the tax system should not distort firms' production decisions, thus maintaining production efficiency. Diamond and Mirrlees (1971) show that even if nondistortionary lump-sum taxes are unavailable (that is, in a "second-best" world), taxes should be such that production decisions remain efficient. To satisfy this condition it is usually argued that a capital income tax should be neutral; that is, all

[17] The full expensing will expire by 2026. Proponents of a long-term stable policy of full expensing have argued for this policy to be made permanent.

[18] These differ from incentives for in-house innovation through R&D tax credits or intellectual property (IP) regimes. Under such IP regimes, or 'patent boxes', income from the exploitation of IP benefits from beneficial tax treatment such as, e.g., a lower rate than the standard statutory tax rate.

[19] Based on 85 countries covered in OECD (2023d) and excluding countries where there were no tax reforms.

returns to capital should face the same METR. In other words, capital income taxes should not be differentiated across different sectors or economic activities. The direct policy implication is that there should be no special tax on gen AI, robots, or other forms of labor-replacing technology. Yet there can be both efficiency and equity reasons to deviate from this principle.[20]

Efficiency considerations: welfare losses from excessive job dislocation. One argument for taxing automation is to mitigate excessive job displacement, which comes at a social cost when technological change unfolds quickly while labor market adaptation is slow because of labor market frictions. Acemoglu, Manera, and Restrepo (2020) develop a task-based model with labor market frictions. In this framework, a robot tax can be desirable to discourage automation at the margin (that is, where automation yields the smallest productivity gains).[21] Credit constraints provide further arguments for taxing automation to internalize the external costs of job displacement. Beraja and Zorzi (2024) show that while this implies an efficiency-based case for taxing automation during a transitional phase, this argument does not hold up in the long run.

Equity considerations: mitigating wage inequality. Another argument for taxing automation is to mitigate wage inequality arising from technological change. If governments do not have access to other tax instruments for redistribution, distorting the adoption of new technologies to influence the wage distribution may be optimal. The underlying idea is that reduced automation increases demand for low-skilled labor and reduces demand for high-skilled workers, which then compresses relative wages—so-called *predistribution* (Guerreiro, Rebelo, and Teles 2022; Costinot and Werning 2023; Thuemmel 2023). Costinot and Werning (2023) estimate the optimal tax rate on robots at between 1 and 3.7 percent of the price of the robots. The more disruptive the new technology, the higher the optimal tax rate.[22] Yet this inequality-based argument may have limited salience in the face of gen AI. For instance, occupations that are most affected by automation through robots are not filled by unskilled workers but rather by middle-skilled routine jobs. In this case, a tax on automation will increase the relative wages for these middle-skilled workers and thus decrease inequality at the top but raise inequality at the bottom. It can then be optimal to either impose a tax or a subsidy on automation (Thuemmel 2023). The implications of a tax on gen AI may have even more variable implications across the skill distribution, making the case for a tax or subsidy ambiguous.

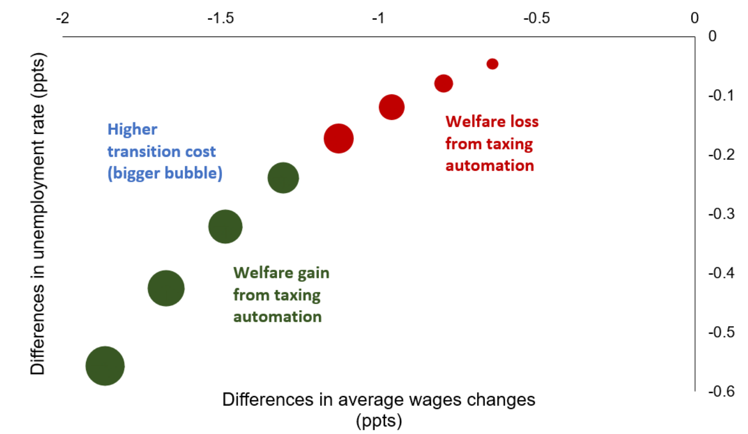
[20] Another reason could be the carbon footprint from AI servers, which require vast amounts of electricity (de Vries 2023). A carbon tax would be the most efficient way to internalize these external costs into the price of the technology. In its absence, however, a tax on AI (or energy used by AI) provides a crude and admittedly less efficient alternative to doing so.

[21] The automation tax is optimal if there are limits to changing general taxes on capital and labor. Without these restrictions, high capital taxes relative to labor taxes are sufficient to efficiently mitigate labor substitution (Box 1 discusses the implications of general taxes for labor and capital from developments in the labor income share).

[22] Other studies look at tax reform, rather than optimal taxation, to illustrate the trade-off between distributional benefits and efficiency costs of robot taxes (Berg and others 2021). Prettner and Strulik (2020) emphasize that robot taxes are not the best tool to redistribute income because of their large cost to growth compared with other policies.

Model-based illustration. Model simulations show that, if the transition costs from labor displacement are high (such as under a highly disruptive AI scenario), a temporary automation tax could improve welfare. The macroeconomic and welfare impacts of taxing automation are analyzed with the same HANK-DGSE model described previously. Figure 12 shows the implications of temporarily taxing automation to finance unemployment insurance benefits during the transition (compared with using labor taxes as a financing source and at varying transition costs).[23] An automation tax increases the cost of using automated capital, thereby discouraging firms from substituting labor with capital. This mitigates the surge in unemployment and yields a short-term welfare gain. However, it comes at the cost of lower wages (averaging over the short-to-medium term) because of lower productivity. The welfare gain comes from internalizing labor market and credit frictions (efficiency grounds) as well as from redistributing income from capital owners to unemployed workers (equity grounds). We find that welfare is likely to fall if transition costs are modest. However, if the transition cost is substantial, taxing automation can improve welfare even if the government has no preference for redistribution (as shown in the largest bubble in Figure 12). Hence, if the pace and depth of the disruptions from gen AI are larger than what we have seen with past automation, the case for taxing gen AI is strengthened.

Figure 12. Taxing Automation versus Taxing Labor Income to Finance Unemployment Support



Source: IMF staff calculations.
Note: The figure compares the effects of financing social policies with a temporary automation tax relative to doing so with a temporary labor income tax. Each bubble shows how shifting to an automation tax changes the response of average wages and the unemployment rate (averaged over 60 quarters). The different bubbles show how the results change with varying transition costs, with larger bubbles corresponding to larger costs. Red bubbles indicate that taxing automation implies a welfare loss relative to taxing labor, while the opposite holds for green bubbles. ppts = percentage points.

Practical considerations. Notwithstanding theoretical arguments, there are practical hurdles in implementing taxes on automation, robots, and gen AI. Implementing such taxes requires that governments identify the technologies (or the capital assets in which they are embodied) that risk displacing labor. However, to codify such characteristics into actual policy is a tall order. Tax systems usually differentiate capital assets by their useful lifespan and other characteristics, but it is not obvious how these distinctions translate into different job tasks and whether they are substitutes for or complements to the new technology. This makes it difficult to define the tax base of a specific technology in practice. Differences in tax rates across assets that are similar can also incentivize relabeling of assets to avoid taxes. From an international perspective, the location of AI assets can be highly mobile so that a

[23] Insofar as a collective unemployment benefit system and ALMPs are needed to address labor market disruptions, laying off a worker imposes a financial cost on society that firms do not internalize. This externality provides a case for "layoff" taxes (Blanchard and Tirole 2008). Yet these taxes can also affect hiring rates and can reduce firm-level productivity, making them less desirable in the long run (Autor, Kerr, and Kugler 2007).

tax can be easily avoided by relocating or producing the AI abroad. A specific tax on gen AI is therefore not recommended.

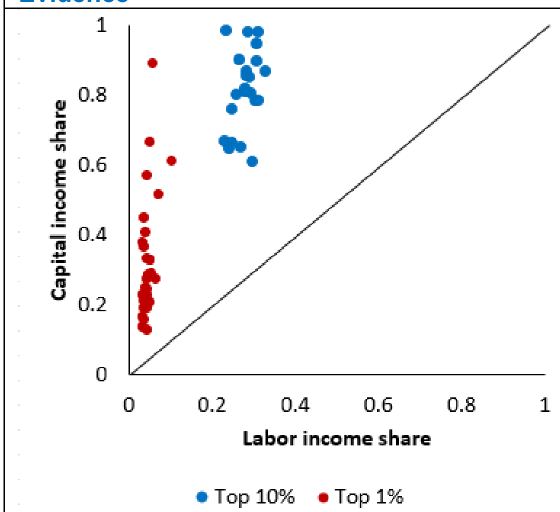
What can be done? As the previous section shows, higher METRs for labor-displacing assets because of corporate tax incentives can in fact mimic an automation tax—which is the case in most countries. Admittedly, such policies could be more distortionary in a scenario where labor disruptions are limited and if applied to broad asset categories that include both labor-saving and labor-augmenting assets. Some countries have corporate tax systems that mimic the opposite of an automation tax and give preferential tax treatment to asset classes that are overall labor-displacing. These regimes could be reconsidered to mitigate excessive labor displacement, which would be especially costly in a more disruptive labor market scenario. Apart from taxes, governments can also include labor market considerations in AI regulation. For instance, the EU AI Act approved by the European Parliament in March 2024 will require employers to notify employees and workers' representatives before implementing "high-risk AI systems."

Broadening the Gains from AI through Taxation

AI makes capital income taxes more important. The taxation of capital income is a controversial issue in public finance. Today's predominant view is that capital income should be taxed to serve both efficiency and equity purposes.[24] AI reinforces these arguments in light of both rising inequality and erosion of the income tax base.

Mitigating rising inequality. Capital income is considerably more concentrated at the top of the income distribution compared with labor income (Figure 13). Hence, a rising capital income share will likely increase inequality. Past innovations have indeed led to rising income and wealth inequality (Aghion and others 2019). Moreover, these innovations gave rise to significant (quasi) rents, which tend to be highly concentrated among a small group of top income earners. If the wider use of gen AI further amplifies these trends, effectively taxing capital income to mitigate rising inequality will become more important.

Figure 13. Concentration of Capital Income among Top Earners: Cross-Country Evidence



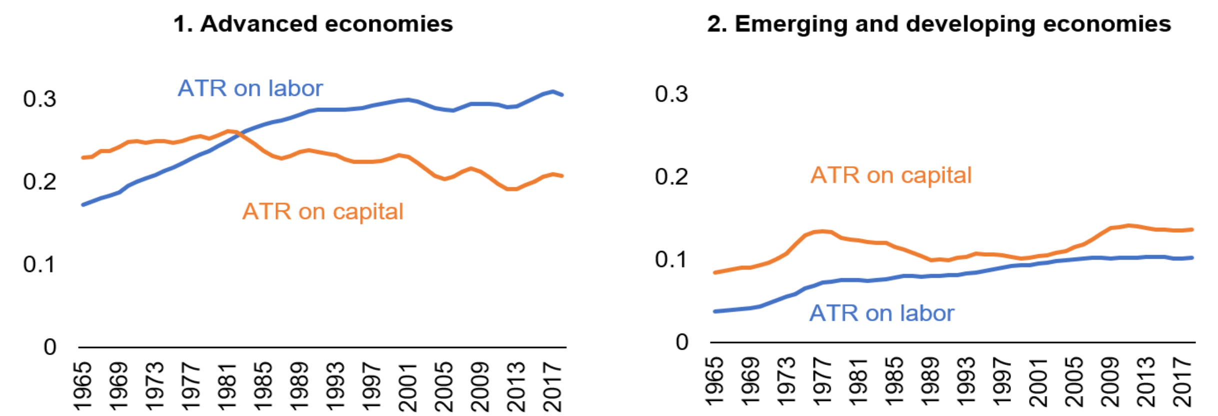
Sources: Luxembourg Income Survey; and IMF staff calculations.
Note: The figure shows the income share held by the top 1 percent and the top 10 percent in labor and capital income in European countries. For example, while the top 10 percent in labor income in European countries earned between 20 and 30 percent of the total, the top 10 percent in capital income earned between 60 and 95 percent of the total. The farther a country is to the left of the 45-degree line, the more concentrated capital income versus labor income.

[24] A classic result in public finance is that the optimal tax on capital income is zero under certain conditions (Atkinson and Stiglitz (1972, 1976); Chamley 1986; Judd 1985). The plausibility of these conditions has recently been challenged, however, and a positive capital income tax is likely to be efficient under alternative, more realistic assumptions (see, for example, Banks and Diamond 2011; Straub and Werning 2020).

Mitigating base erosion. Lower effective taxation of capital relative to labor in many countries risks eroding the income tax base. For instance, since it is difficult to distinguish between the source of income earned by self-employed entrepreneurs, a lower tax on capital income relative to labor induces entrepreneurs to label their income as capital income to minimize their tax burden (de Mooij and Nicodème 2008; Devereux, Liu, and Loretz 2014). Such base erosion will be amplified when the labor income share would drop further as a result of gen AI. This makes effective taxation of capital income at a similar rate as labor income increasingly relevant to mitigate base erosion and sustain public revenue, especially in light of the increasing needs to finance expenditures for upgraded social protection systems.

Declining tax burden on capital. The average tax burden on capital income—measured by corporate and personal taxes on capital as a share of capital income—has consistently declined in advanced economies since the 1980s (Figure 14). At the same time, the average tax burden on labor—measured by personal taxes on labor and social security contributions as a ratio of labor income—has steadily increased. Whereas capital and labor income were taxed at similar average rates in the early 1980s, the gap had grown to almost 10 percentage points in 2018. However, there is significant cross-country heterogeneity (Annex Figure 2.3). For instance, in Canada, Germany, Japan, the United Kingdom, and the United States, the decline in the average capital tax was significant until 2018. In other countries, such as France and Italy, the gap has also increased, but mainly as a result of the rise in the average tax on labor; the average capital tax has been more stable. In emerging market and developing economies, average tax rates on both labor and capital are generally much lower than in advanced economies. Capital income is generally taxed more than labor income—reflecting the often-smaller coverage of the personal income tax and the relative importance of the corporate income tax in these countries (see panel 2 in Figure 14).

Figure 14. Average Tax Rates on Labor and Capital Income, Five-Year Moving Average
(Percent)



Sources: Bachas and others 2022; and IMF staff calculations.
Note: ATRs are constructed by relating historical data on taxes paid to a measure of the tax base, based on global macroeconomic data covering 1965–2018 (https://globaltaxation.world/). See Annex 2. ATR = average tax rate.

Policy measures. To reverse the declining trend in capital income taxation, countries can consider various measures to strengthen their systems, including the following:[25]

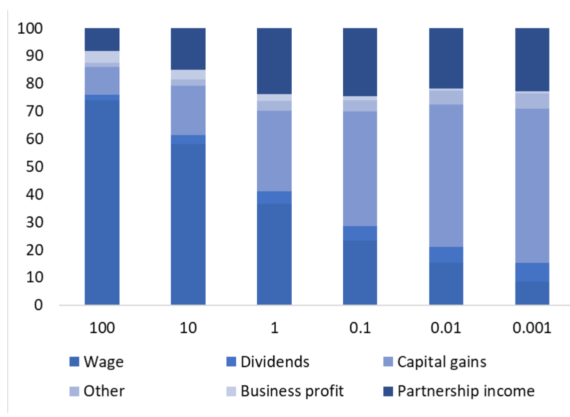
- **Strengthening the corporate income tax.** The CIT is an effective withholding mechanism for the taxation of capital income but has come under severe pressure from international profit shifting and tax competition. The global minimum tax, as agreed on by the members of the Inclusive Framework, will reduce pressures of tax competition for all countries and forestall a race to the bottom in CIT (Hebous and Keen 2023). Thus, it might enable countries to reverse past reductions in effective tax rates.

- **Effective taxation of economic rents.** Rising profits as a result of gen AI may call for a supplemental tax on excess profits from monopoly rents (see, for example, Hebous, Prihardini, and Vernon 2022). These do not need to be targeted to AI companies but could apply more generally. A common approach between countries would mitigate the risk of cross-border profit shifting, which could be significant in light of the intangible nature of gen AI assets.

- **Improving enforcement.** Capital income taxes have been under pressure from tax evasion, especially to offshore low-tax countries or jurisdictions with strict secrecy standards. Recent global developments facilitating exchange of information for tax purposes between countries, especially automatic exchange of information (AEOI) under the initiative of the Group of Twenty and the US Foreign Account Tax Compliance Act (FATCA), have already helped effectively counter offshore tax evasion (EUTAX 2024). Gen AI can further enhance this enforcement through more effective use of information to counter tax fraud. Such improved enforcement will also enable countries to design better systems of capital income taxation, with higher effective rates.

- **Enhancing capital gains taxation.** Capital gains are often taxed less than other forms of capital income, primarily because they are taxed only when realized, allowing for deferral of tax liabilities. In some countries, capital gains are partially or fully exempt from personal income tax[26] or taxed less if an asset is held for more than a specific period. Moreover, certain types of returns (for example, on government bonds) and certain investors (for example, institutional investors) receive preferential treatment. At

Figure 15. Income Share by Source and Income Groups in the United States



Source: US Internal Revenue Service.
Note: The figure shows the sources of income among different income groups, from the overall average to the top percent of the income distribution.

[25] See Hebous and others (2024) for a comprehensive discussion on how to effectively tax capital income and/or wealth, including through taxes on wealth and wealth transfers.

[26] In the US, assets transferred at death receive a step up to their market value, implying that gains up to that point become effectively exempt.

the same time, capital gains are highly concentrated among top income earners (Figure 15). Enhancing the taxation of capital gains thus presents an opportunity to mitigate inequality while bolstering revenue to support additional redistributive measures.

Should labor be taxed less? Whereas across-the-board tax cuts on labor might be too expensive, targeted income tax credits for workers or job credits for employers could alleviate the relative tax burden on certain types of labor compared with capital. Income tax credits—such as the Earned Income Tax Credit (EITC) in the United States—have been effectively targeted to low-income earners. To be effective in reducing job displacement, they should at least partially reduce labor costs for employers—which tends to be the case in the United States (Nichols and Rothstein 2015). Targeting specific sectors prone to excessive job displacement could be more challenging given the potentially pervasive and variable impact of the new technologies on labor. Moreover, practical obstacles may arise in relation to employment credits if firms could relabel new positions to gain eligibility, as was recently observed in the United States (Gurmu, Sjoquist, and Wheeler 2021; Chirinko and Wilson 2023).

Funding for AI Innovation and Deployment

Fiscal policies as drivers of AI innovation. Current advances in AI are the fruit of decades-long investment in fundamental research, often benefiting from publicly funded programs (for example, AI Next and AI Institutes in the United States and the European Union's partnership on AI, data, and robotics), subsidies, and research and development grants to firms. As discussed earlier, tax policies have also encouraged investment in AI to different degrees across countries. Should fiscal policies continue to be used to finance AI innovation and deployment?

Funding for AI innovation. Global corporate investment in AI has soared more than tenfold in the past decade. After decades of public and private research, AI technology has matured to the commercial adoption phase, suggesting that fiscal support for overall innovation in AI is now less of a priority in advanced economies. Governments should instead focus on areas where social returns are greater than private returns and lead to insufficient private investment. These include funding fundamental research with broader applications, providing the necessary infrastructure (for example, digital connectivity, electricity grids), particularly in emerging market and developing economies, and promoting AI applications in the public sector (education, health, government administration), where productivity has faltered and consumer costs have surged in past decades. Favoring applications that expand, rather than substitute for, human capabilities (Acemoglu, Autor, and Johnson 2023) is desirable in theory but may not be feasible with existing levels of administrative capacity, even in advanced economies. Instead, the focus can be on funding innovative upskilling and re-skilling programs and strengthening social protection systems more broadly.

Considerable scope for enhancing AI deployment in emerging market and developing economies. From high-quality education and learning, through precisely targeted and individually customized human capital investments, to improved access to financial services, AI could be deployed to improve development outcomes in emerging market and developing economies. AI could also help provide cost-effective solutions to deliver social services to those who need them most, including remote communities.

Other opportunities include risk management—disease prevention, natural disaster management, and humanitarian crisis management—which tends to be weaker in emerging market and developing economies. In addition to weaknesses in the digital infrastructure, critical constraints on adoption of AI solutions include lack of a developed digital economy and a supporting entrepreneurial ecosystem and scarce local AI expertise—highlighting a role for governments to close gaps.

Need to upgrade administrative and governance capacity. Effectively directing AI innovation can be a tall order (IMF 2024), not least because AI technology is undergoing rapid change and applications of specific technologies are hard to predict. Governments must upgrade their capabilities, investing in expertise to be able to select and vet funding to projects and update regulation as the speed, autonomy, and opacity of AI systems challenge traditional models of regulation. National investment in talent, data, and computer resources, as well as in national procurement capacity, will complement these upgrades. A dedicated agency, inspired by the model of the US National Institutes of Health, that mobilizes the private sector, academia, and other stakeholders could track AI developments and use. Such an institution could help develop a broader accountability framework for companies that build, deploy, and control AI, as well as for downstream users. The centrality of data governance suggests that AI governance cannot be divorced from the governance of data and the promotion of data commons. Given the global reach of AI technologies and high cross-border spillovers, policy initiatives should seek international collaboration. To this end, the European Organization for Nuclear Research (CERN), which operates the largest particle physics laboratory in the world, and similar international scientific collaborations may offer useful lessons (United Nations 2023). A "distributed CERN," reimagined for AI, could expand opportunities for international cooperation on innovation, use, and regulation.

Conclusions and Policy Implications

Forward-thinking policies. Many questions remain about what gen AI will mean for labor markets and economies at large in the coming decades. Will lower-skilled workers gain on higher-skilled workers? What kinds of new jobs will emerge? Will opportunity and wage inequality increase or decrease? Given the tremendous uncertainty about the speed of AI progress and its economic impact in the short, medium, and long term, policymakers must be prepared for alternative scenarios (Korinek and Suh 2024). If AI supports workers by raising labor productivity and creating new job opportunities, policy responses will differ markedly from a scenario in which AI rapidly displaces jobs, reduces wages, and increases inequality. And not all countries are likely to be affected equally. While the answers are not yet certain, countries will need to assess whether their social protection, education, and tax systems are fit for purpose and flexible enough to cope with a wide range of potential scenarios.

The future of social protection. AI-induced labor market transformations have the potential to redefine employment and reshape the skills demanded by employers, which will require a comprehensive reassessment of labor policies and social protection mechanisms. If AI acts like general-purpose technologies (for example, steam engines, electricity), then a range of work tasks will be automated but new opportunities will arise as well. In this case, current social protection systems provide a solid foundation, particularly in advanced economies. Unemployment insurance eligibility rules should be robust and resilient to radical uncertainty and coverage should be broadened to encompass self-employed workers and those with atypical employment contracts. ALMPs should aim to improve skill acquisition for those capable of adapting to new market requirements, while social assistance benefits should target those permanently displaced or indirectly affected by labor market disruptions. Sector-based training, apprenticeships, and upskilling and re-skilling programs could play a greater role in helping workers move to new tasks and sectors. A future scenario in which the nature of work changes dramatically (for example, if tasks became increasingly unnecessary) would also require gains to be shared more widely, using unconditional transfers, which suggest a need to consider the design and infrastructure required for such policies. AI itself could be leveraged to radically improve the efficiency and quality of social protection systems in conjunction with traditional systems to reduce data privacy risks.

Educational systems. Education and training policies should be geared to upskilling workers to cope with structural changes in the workplace and to matching the skill and task demands of new technologies (OECD 2023c). This is also essential to ensure societies can harness the full potential of AI. While spending matters, the quality and adaptability of education will make the difference in preparing workers for change. Given the high uncertainty about which skills are needed at any point in time, educational systems need to be flexible in responding to market demands, keeping equity and access in mind. Educational systems themselves could take advantage of gen AI to foster higher-level skills such as critical thinking, analysis, and strategy. But developments in gen AI and robotics will require that people develop skills to work alongside AI systems and not just existing technologies.

Taxing AI. A special tax on gen AI to reduce its speed of adoption and prevent excessive labor displacement will be hard to design and implement and would run the risk of hampering productivity growth, including in areas where AI investment augments labor. Yet it is recommended that countries reconsider the design of current corporate tax systems in how they incentivize investments in automation. For instance, tax incentives in the form of capital allowances may need to be reconsidered in countries where they are more generously applied to labor-displacing software or intangibles than to other assets. At the same time, countries where corporate tax systems impose much higher tax burdens on AI may hold up deployment and reduce productivity growth. Income tax credits and job credits could also be considered to mitigate excessive labor displacement from automation, even if they cannot be targeted to particular occupations. Finally, given the large amount of energy consumed by AI servers, taxing the associated carbon emissions is a good way to reflect the external environmental costs in the price of the technology.

Capital taxation. The average tax on capital income has declined in advanced economies during the past few decades. It is important that countries reverse this trend, especially under a disruptive AI scenario. First, low taxation of capital compared with labor can contribute to excessive labor displacement and exacerbate labor market frictions. Second, capital income taxes are essential to address the increasing inequality associated with rising market power and economic rents enjoyed by dominant firms in winner-take-all markets. Third, large labor displacements that reduce the labor income share will erode the tax base and reduce public revenue. Enhancing capital income taxes will not only prevent this but will boost revenue mobilization—which is necessary to finance higher education and social spending with the arrival of automation. More effective taxation of capital income requires restoration of the corporate income tax and calls for well-designed excess profit taxes, higher personal income taxes on capital through better enforcement of automatic information exchange between countries, and enhanced taxation of capital gains.

Advancing tax systems through gen AI. Digital transformations in revenue administration have already visibly reduced tax evasion around the world (Amaglobeli and others 2023). Gen AI has significant potential to further advance tax administration practices to improve tax enforcement, given the critical role of information and data. The AI-associated information revolution can ultimately enable tax system redesign. Information constraints are at the heart of the theory of "second-best"; by transforming information systems and management, gen AI will turn classic tax theory upside down and urge a rethink of the old ways of doing things. It may, for instance, usher in the design of a personalized progressive value-added tax, an income tax based on lifetime income, or a real-time market-value-based property tax.

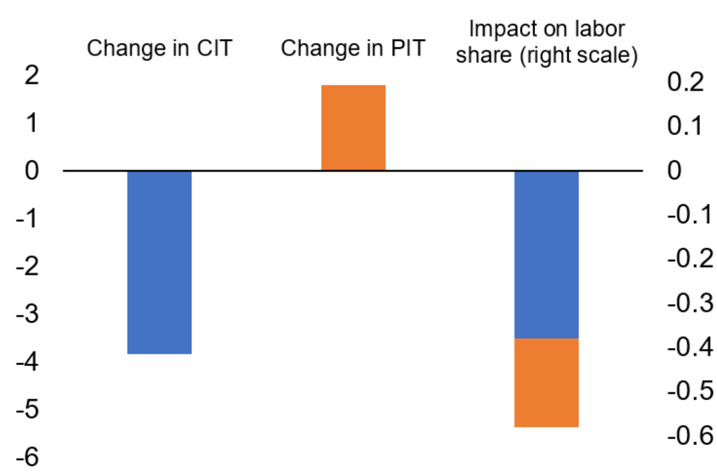
AI that serves people. Fiscal policies can promote innovation and deployment of AI in applications with greater social benefits, such as those that improve the quality of social services (education, health care, government). Finding the right policy response in a highly uncertain world of AI will require upgrading administrative and analytical capacity to monitor and evaluate trends in technological advances. Policies to steer and cushion the implications of AI will depend on how future scenarios unfold. Ensuring that AI is deployed for the common good, and that its benefits are distributed equitably, will require governmental and intergovernmental action, with innovative ways to motivate participation by the private sector, academia, and civil society. Innovation and deployment policies should thus work in tandem with social protection, education, and tax and regulatory policies to broaden the gains of gen AI for all.

Box 1. Taxation and the Decline of the Labor Income Share

The labor income share has fallen steadily since the 1980s in most advanced economies. Some have argued that declining corporate income tax (CIT) rates explain part of this development. There are several channels through which the CIT can impact the labor income share. For instance, a lower CIT rate can boost investment so that the income share of labor decreases. This holds especially for investment in labor-substituting capital, which reduces employment and wages (Kaymak and Schott 2023; Acemoglu and others 2020). Yet capital and labor can also be complementary, so that more capital leads to higher labor productivity and higher wages, thus offsetting the decrease in the labor income share (Fuest, Peichl, and Siegloch 2018; Garrett, Ohrn, and Suárez Serrato 2020). A lower CIT rate can also induce self-employed entrepreneurs to report their income as profits instead of wages so that the capital share artificially increases (de Mooij and Nicodème 2008; Devereux, Liu, and Loretz 2014). On balance, the impact of the CIT on the labor income share is an empirical question.

A panel regression of 42 advanced and emerging market economies shows that, conditioning on other macroeconomic determinants, the CIT rate has a positive and significant impact on the labor income share (Annex 3). For each percentage point reduction in the statutory CIT rate, the labor share falls 0.1 percent. In comparison, for each percentage point reduction in the top statutory PIT rate, the labor share increases 0.11 percent. Thus, the reduction in the average statutory CIT rate in the past two decades (from 27.7 to 23.9 percent during 2005–18), combined with a slight increase in the average top PIT rate (from 41.9 to 43.7 percent), is estimated to have reduced the labor share by 0.58 percentage point in advanced economies over this period.

Box Figure 1.1. Declining Labor Share: Role of Taxation
(Percentage points)



Sources: Bachas and others 2022; IMF, World Economic Outlook database; and IMF staff calculations.
Note: The figure shows the cumulative changes in the corporate and personal income tax rates, respectively, for 32 advanced economies during 2005–18 and their estimated impact on the labor share. CIT = corporate income tax; PIT = personal income tax.

Annex 1. Model Framework

The analysis extends a tractable HANK-DGSE model with labor market frictions developed by Ravn and Sterk (2021) to incorporate automation. The economy has two intermediate sectors that employ labor, traditional capital, and automated capital. Automated capital differs from traditional capital in that it can substitute for labor, following Berg, Buffie, and Zanna (2018). The two sectors are initially identical, but we assume that only one is subject to an automation shock in order to capture cross-sector labor flows and study policies supporting sectoral mobility. The output of the two intermediate sectors is combined to produce a final good.

The labor market is subject to search and matching frictions following the Diamond-Mortensen-Pissarides tradition. Three types of households are modeled: firm owners, employed workers, and unemployed workers. Unemployed workers can search for jobs in either sector, but sectoral reallocation can be costly—for instance, because of a potential mismatch between the skills of the unemployed workers and those required by firms (Branch, Petrosky-Nadeau, and Rocheteau 2016; Di Pace and Hertweck 2019; Walsh 2011). Because of these labor market frictions, job prospects are uncertain, exposing households to idiosyncratic income risk. Employed workers are not fully insured against this risk and, therefore, attempt to self-insure through precautionary saving.

Policy tools modeled include unemployment insurance and active labor market policies designed to facilitate sectoral mobility. These policies are funded with labor income taxes, ensuring budget neutrality each period. Other standard features include nominal rigidities and a Taylor-rule-based interest rate.

The following equations describe the production structure and labor market dynamics.

Sectoral production: Intermediate sector $i = \{1,2\}$ good is produced by combining traditional capital k_t^i, automated capital m_t^i, and labor n_t^i with a constant elasticity of substitution (CES) function with elasticity η_i and traditional capital share α_i:

$$y_t^i = \left(\alpha_i^{1/\eta_i}\left(k_{t-1}^i\right)^{(\eta_i-1)/\eta_i} + (1-\alpha_i)^{1/\eta_i}\left(v_t^i\right)^{(\eta_i-1)/\eta_i}\right)^{\eta_i/(\eta_i-1)},$$

in which v_t^i represents the CES bundle between labor and automated capital, with elasticity η_{iv} and labor share s_i:

$$v_t^i = \left(s_i^{1/\eta_{iv}}\left(n_t^i\right)^{(\eta_{iv}-1)/\eta_{iv}} + (1-s_i)^{1/\eta_{iv}}\left(A_t^{im}\, m_{t-1}^i\right)^{(\eta_{iv}-1)/\eta_{iv}}\right)^{\eta_{iv}/(\eta_{iv}-1)},$$

and A_t^{im} denotes the productivity of automated capital.

Final goods are produced using inputs from the two intermediate sectors with a Cobb-Douglas production function[27]:

$$y_t = A_t (y_t^1)^{\varsigma} (y_t^2)^{1-\varsigma},$$

in which A_t denotes aggregate total factor productivity.

[27] Using a CES function with equal shares of the two sectors and an elasticity of 0.9 results in similar findings.

Labor market dynamics: The value of being employed in sector i, E_t^i, is a function of the Nash bargained wage w_t^i subject to the labor income tax rate τ_t, the beginning-of-period match destruction rate ρ, the probability of finding a job in the same quarter of job separation in each sector, and the transition probability from employment to unemployment $z_t = \rho(1 - f_t)$[28]:

$$E_t^i = (1 - \tau_t)w_t^i + \beta((1 - \rho)E_{t+1}^i + \rho\,(f_{t+1}^i\,E_{t+1}^i + f_{t+1}^j\,E_{t+1}^j) + z_{t+1}\,U_{t+1}^i).$$

The value of being unemployed after having worked in sector *i*, U_t^i, is a function of the unemployment benefit ub_t^i and the probability of finding a job next period in different sectors.

$$U_t^i = ub_t^i + \beta((1 - f_t)U_{t+1}^i + f_{t+1}^i\,E_{t+1}^i + f_{t+1}^j\,E_{t+1}^j).$$

The unemployment benefit ub_t^i is modeled as

$$ub_t^i = rrat_t\,w_{t-1}^i + ro\,\overline{w}\ ,$$

in which $rrat_t$ is a policy parameter capturing the replacement ratio of the previous wage' i.e., the larger $rrat_t$ the higher the unemployment generosity. The government can adjust the replacement ratio over time, as discussed below. Meanwhile, the second term in the equation is a constant reflecting other benefits of being unemployed (such as home production).

In each sector, there is a representative "labor firm" that sells labor services to intermediate goods firms at a price x_t^i. The labor firms hire workers by posting vacancies. Posting a vacancy involves a fixed cost, κ > 0, which is paid in every period the vacancy is open. To model frictions in sectoral mobility, the labor firm is assumed to have a cost of hiring new workers tc_t^i , for instance due to retraining needs. Active labor market policy $ALMP_t$ is assumed to reduce this hiring cost. The value of an open vacancy is

$$J_t^i = x_t^i - w_t^i - tc_t^i\,(1 - ALMP_t) + \beta(1 - \rho)\,J_{t+1}^i,$$

in which tc_t^i is assumed to follow $tc_t^i = \rho_{tc}tc_{t-1}^i + (1 - \rho_{tc})\gamma\,w_t^{Ni}\varepsilon_{tct}^i$, with ρ_{tc} reflecting the persistence of the cost, γ relating the cost to the wage, and $\varepsilon_{tct}^i = \{0,1\}$ to capture periods during which the cost is incurred.

Note that the value of having an open vacancy is based on the "free-entry condition": the labor firm posts vacancies if the value of having a vacancy exceeds the cost. Therefore, the net value of opening a vacancy is driven to zero in equilibrium, or: $J_t^i = \frac{\kappa}{fv_t^i}$, in which fv_t^i is the probability of filling a vacancy in sector *i.*

Calibration

Annex Table 1.1 presents the calibration of the key parameters of the model. Specifically, the separation rate ρ*,* matching efficiency $\overline{m}$, and matching elasticity μ are calibrated to match three targets: (1) unemployment rate of 7 percent, which ranges between 5 percent in the US and 10 percent in euro area countries; (2) job-finding probability of workers of 45 percent per quarter; and(3) vacancy-filling probability of firms of 70 percent per quarter (Christoffel, Kuester, and Linzert 2009; Challe 2020). The replacement ratio is set at 50 percent. The benefits of unemployment beyond unemployment insurance are calibrated to match a 20–30 percent consumption loss upon unemployment (Den Haan, Rendahl, and Riegler 2018). The calibration of other parameters is explained in Annex Table 1.1.

[28] This reflects the probability of being separated at the beginning of the period (ρ) and not finding a job in the same period ($1 - f_t$).

This baseline simulation calibrates a series of shocks that increase the productivity of automated capital by 300 percent by 2030, resulting in a decrease of labor in the affected sector by 20 percent. This is consistent with McKinsey (2023)'s projection that automation could replace the time spent on work activities by 20 to 30 percent by 2030. Note however that the projection includes both the extensive and intensive margins, whereas the model captures only the extensive margin.

Annex Table 1.1. Calibration of Model Parameters

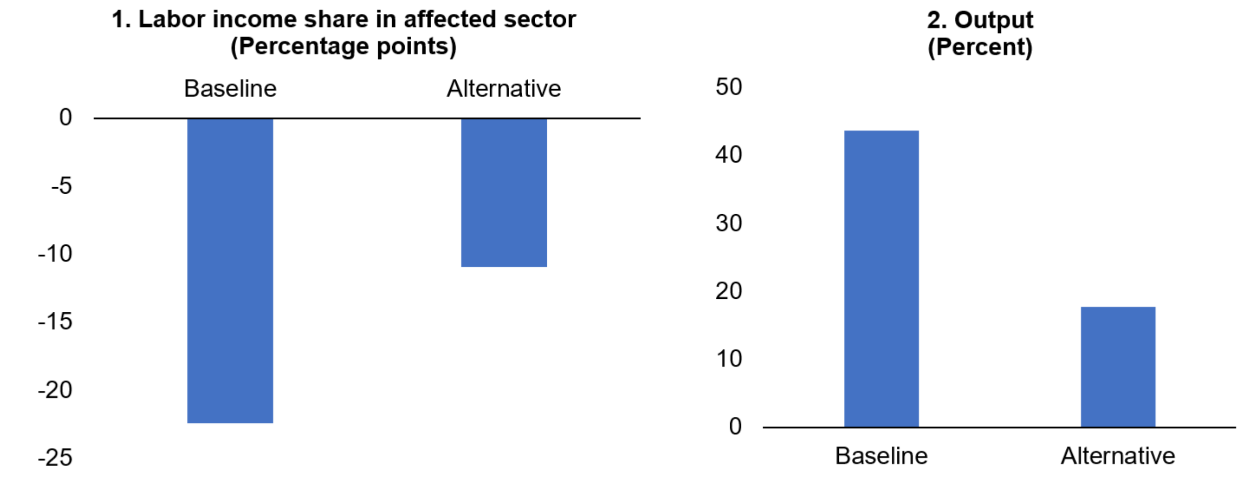
Parameters	Symbol	Value	Sources
Sectoral Production Parameters			
Elasticity of substitution in labor-automated capital (LAC) bundle	η_{iv}	2.5	Berg, Buffie, and Zanna (2018)
Elasticity between traditional capital and the LAC in sectoral production	η_i	0.50	Berg, Buffie, and Zanna (2018)
Share of labor in LAC bundle	s_i	0.99	Labor income share of 61 percent
Share of traditional capital in sectoral production	α_i	0.54	Traditional capital income share of 35 percent
Share of sectoral input in final goods production	ς	0.5	Assumption of symmetric sectors
Labor Market Parameters			
Separation rate	ρ	0.06	See text for discussion
Matching efficiency	$\bar{m}$	0.56	See text for discussion
Matching elasticity	μ	0.5	See text for discussion
Vacancy cost	κ	0.04	About 15 percent of average wage as in standard value
Worker's wage bargaining power	ψ	0.65	Standard value
Replacement rate initial value	$rrat$	0.5	See text for discussion
Other benefit of unemployed worker	ro	0.26	See text for discussion
Response of unemployment income support to unemployment rate	λ	0.4	See discussion in scenario
Persistence of hiring cost	ρ_{tc}	0.5	See discussion in scenario
Hiring cost parameter	γ	0.15	See discussion in scenario
Macroeconomic Parameters			
Discount factor	β	0.989	Challe (2020)
Firm owners' risk aversion	$\tilde{\sigma}$	0.283	Challe (2020)
Depreciation rate	δ	0.025	Standard value
Price elasticity	ϵ_p	6	Standard value
Price adjustment cost	κ	30	Match the average frequency of price changes (every three quarters)
Taylor rule: smoothing	ρ	0.5	Standard value
Taylor rule: response to inflation	γ_π	2	Standard value
Taylor rule: response to output gap	γ_y	0.125	Standard value

Source: IMF staff compilation.
Note: Standard values are based on Smets and Wouters (2007); Christiano, Eichenbaum, and Evans (2005); Gomes, Jacquinot, and Pisani (2012); and Gertler, Sala, and Trigari (2008).

Smaller Impact Scenario

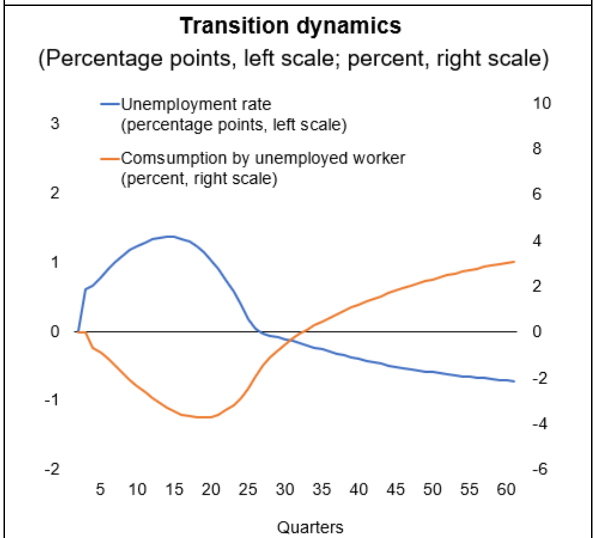
The alternative scenario considers a smaller increase in the productivity of automated capital—about half the magnitude of that in the baseline presented in Figure 4—similar to Cazzaniga and others (2024). Under this assumption, output increases by about 17 percent, while the labor income share in the affected sector falls by 10 percentage points, reducing total labor income share in the economy by 5 percentage points (Annex Figure 1.1). The same qualitative results remain. The transition is still costly due to sectoral mobility frictions, but less severe than in the baseline (Annex Figure 1.2).

Annex Figure 1.1. Alternative Scenario with Smaller Sectoral Automation Shocks



Source: IMF staff calculations.
Note: In the alternative scenario, sectoral productivity shocks to automated capital are about half the magnitude of those in the baseline scenario.

Annex Figure 1.2. Transitional Dynamics in the Alternative Scenario



Source: IMF staff calculations.
Note: In the alternative scenario, sectoral productivity shocks to automated capital are about half those of the baseline scenarios.

Annex 2. Effective Tax Rates

This annex discusses details of two tax measures used in the analysis: marginal effective tax rates obtained from simulations of countries' prevailing tax rules and average tax rates, obtained from macroeconomic data.

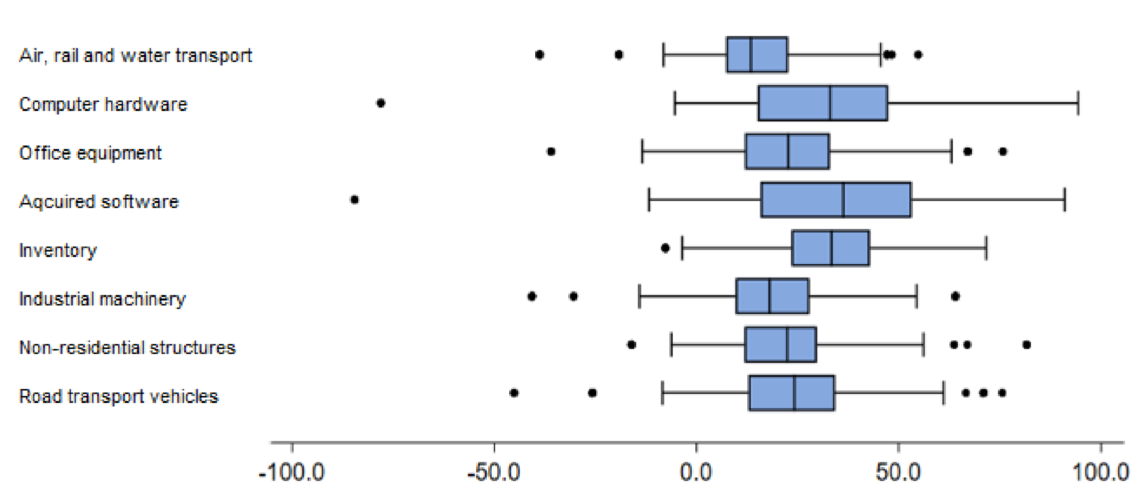
Marginal Effective Tax Rates

The effective tax burden of the corporate income tax (CIT) depends not only on the statutory CIT rate but also on detailed depreciation rules for various asset types and other capital allowances. Many countries aim to match tax depreciation to economic depreciation. Yet accelerated (or bonus) depreciation for tax purposes has been used extensively to support particular investments that are deemed to have positive spillovers. For instance, the US and the UK allow investments in some tangible assets to be expensed immediately. Such provisions can have significant implications for investment because of the time value of money.

Incentives for incremental investment decisions by firms can be measured by the marginal effective tax rate (METR). It captures firms' investment incentives at the point at which the marginal product of capital equals the cost of capital—that is, at the breakeven point. This margin determines the scale of investment. METRs can be calculated for investments in alternative assets and different sources of finance, using parameters in the tax code for the tax rate, tax depreciation, deductions for financing costs, and other capital allowances or tax credits. If METRs are zero, this means that the tax system is neutral regarding investment; if METRs are positive but equivalent across asset types, the tax system distorts overall investment but not the allocation between assets. By exploring the variation in METRs for different asset types, one can gauge the tax preference for certain asset types over others.

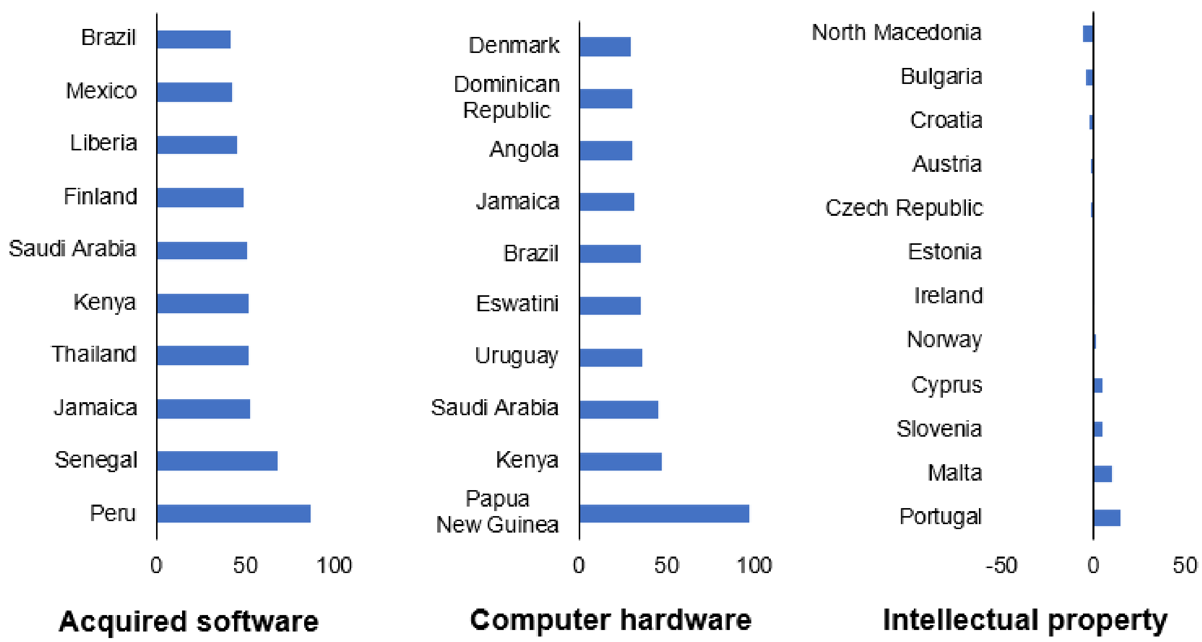
Two internationally comparable datasets on METRs published by the Organisation for Economic Co-operation and Development (OECD) and the ZEW Leibniz Centre for European Economic Research are used in this note. Both contain METRs for various countries, asset groups, and time periods and are based on the same methodological approach. The ZEW data cover three main assets (buildings, machinery, acquired patents) for 34 countries over the period 1998–2020. The OECD data cover eight different assets (including acquired software and computer hardware; see Annex Figure 2.1) for 74 countries over the period 2017–22. Annex Figure 2.1 shows that current METRs (based on equity finance and averaged across 74 countries) are far from neutral across asset types. The averages are well above zero, with the bulk of observations in the range of 12.5 to 35 percent.

Annex Figure 2.1. METRs by Asset Group, 2017–22, 74 Countries
(Percent)



Sources: Organisation for Economic Co-operation and Development; and IMF staff calculations.
Note: METR = marginal effective tax rate.

Annex Figure 2.2. Corporate Tax Bias for Labor-Saving Assets by Economy: Bottom 10
(Percent)



Sources: Organisation for Economic Co-operation and Development; ZEW Leibniz Centre for European Economic Research; and IMF staff calculations.
Note: The figure shows the 10 economies with the least corporate tax bias favoring labor-saving assets. The bias is measured as the METR for each asset type relative to the METR for buildings and is based on a sample of 85 economies for 2022 for acquired software and computer hardware; for intellectual property the sample covers only the EU27 for 2020. A negative (positive) value denotes a lower (higher) METR on the asset relative to buildings. METR = marginal effective tax rate.

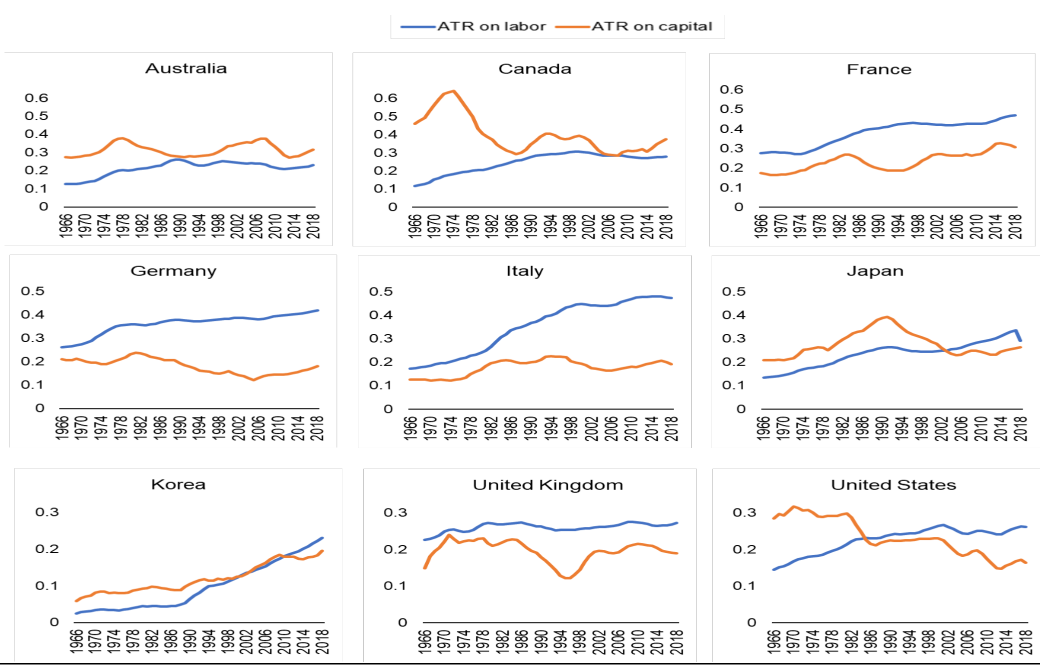
Average Tax Rates

Average tax rates (ATRs) are constructed by relating historical data on taxes paid to a measure of the tax base. The ATRs used in this note are based on macroeconomic data compiled by Bachas and others (2022), who develop a long global time series of ATRs on capital and labor. Based on this approach, each tax category, as captured in the macroeconomic data, is attributed to one of the two production factors.

The tax revenue data are structured according to the methodology in OECD Revenue Statistics (OECD 2023e), with category 1200 (CIT) fully attributed to capital, category 2000 (social security contributions [SSC]) fully attributed to labor, and category 1100 (personal income tax [PIT]) attributed partially to capital and partially to labor. The PIT share attributed to capital and labor varies by country and year. Although the definition of the ATR on labor income follows Bachas and others (2022), we apply a different definition of the ATR on capital income by excluding property and wealth taxes to better reflect taxes affecting firms' automation decisions. Consumption taxes are excluded from the analysis. Having attributed each tax to one of the two production factors, totals are divided by the capital and labor income shares computed from the national accounts data.

Further disaggregating the ATRs into their components shows that the ATR on corporate income and on capital income (at the personal level) have both decreased since 1980, with the latter experiencing significant reduction in the early 1980s and in the early 2000s. The CIT component is more affected by business cycles and has been on a downward trajectory since the late 1970s. Since 2016, automatic exchange of bank information may have played a role in a slight recovery of the personal tax components. Annex Figure 2.3 shows trends in the ATRs for labor and capital in individual countries.

Annex Figure 2.3. ATR on Labor and Capital for Individual Countries



Sources: Organisation for Economic Co-operation and Development; and IMF staff calculations.

Annex 3. Corporate Taxes and Labor Income Share

This annex presents details on the empirical analysis, examining the effect of corporate taxes on labor income share across countries.

Data

Labor income share. A long time series of labor income shares for 155 countries since 1965 is available from Bachas and others (2022). It uses a panel of national accounts data from the System of National Accounts (SNA), produced by the United Nations. Estimation of labor income shares requires information on all the components of national income, including compensation of employees plus a share of mixed income (operating surplus of private unincorporated enterprises). While it is relatively straightforward to measure workers' compensation, the labor share of mixed income (unincorporated enterprises) is hard to measure. The benchmark series of the labor share of mixed income is assumed at 75 percent; that is, 25 percent of mixed income is considered capital income. Given that the labor share of mixed income is time- and country-invariant, the identifying variation in the labor income share comes from changes in the workers' compensation across countries and years.

Country-level tax rates and macroeconomic variables. Data on statutory corporate and personal income tax rates come from IMF Fiscal Affairs Department Tax Rate Database. Data on nontax macroeconomic determinants of labor income, including average hourly wage, average price of capital relative to consumption, trade openness, population, financial development index, and inflation are obtained from the IMF World Economic Outlook database.

Specification

The baseline specification evaluates the impact of corporate and personal income taxes on labor income share, controlling for the standard determinants of labor income share for 42 advanced and emerging market economies during 1990–2008:

$$LS_{it} = \beta_1 CIT_{it} + \beta_2 PIT_{it} + \Lambda' X_{it} + \alpha_i + \eta_t + \varepsilon_{it},$$

in which LS_{it} corresponds to the labor income share in country *i* year *t*; X_{it} is a vector of structural and institutional characteristics, including labor costs, defined as the log of average labor income per hour worked (US dollars, constant prices); capital costs, defined as the average price of capital relative to consumption; trade openness, defined as the sum of a recipient country's exports and imports as a share of GDP; and level of financial development. CIT_{it} denotes the statutory corporate income tax rate, and PIT_{it} denotes the top statutory personal income tax. The regression also includes country and year fixed effects, α_i and η_t, respectively. ε_{it} denotes the error term.

Results

The results are summarized in Annex Table 3.1, with results for only advanced economies in specification (3), discussed in Box 1. Estimated coefficients for the CIT rate are positive and insignificant if all countries are included in specifications (1) and (2). This masks a positive and significant (at the 90 percent level) CIT coefficient for advanced economies in specification (3) and a negative and insignificant CIT coefficient for emerging market and developing economies in (4). In contrast, the estimated coefficients for the PIT rates are negative and significant in specifications (2)–(4). Based on the results from specification (3), a 1 percentage point reduction in the statutory CIT rate, all else equal, reduces the labor income share in advanced economies by 0.1 percentage point. A 1 percentage point reduction in the top statutory PIT rate, in comparison, increases the labor income share by 0.11 percentage point. The average statutory CIT rate decreased from 27.7 to 23.9 percent in the sample of 32 advanced countries during 2005–18, or by 3.8 percentage points. The average top statutory PIT rate increased from 41.9 to 43.7 percent during the same period, or by 1.8 percentage points. Together, these would imply a reduction in labor share of 0.58 percent, all else constant (Box Figure 1.1).

Annex Table 3.1. Estimation Results

	(1)	(2)	(3)	(4)
Statutory CIT rate	0.01	0.02	0.10*	-0.01
	(0.02)	(0.02)	(0.06)	(0.03)
Statutory PIT rate		-0.04**	-0.11***	-0.06**
		(0.02)	(0.04)	(0.03)
Controls included	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	1086	1086	399	687
R squared	0.89	0.89	0.93	0.91

Sources: Bachas and others 2022; IMF, World Economic Outlook database; and IMF staff calculations,
Note: IMF staff calculations are based on an ordinary least squares panel regression with country and year fixed effects, controlling for macroeconomic factors and the CIT and PIT rate. The sample covers 42 advanced and emerging market economies during 1990–2018. Values in parentheses indicate standard errors. Column 1 includes only the statutory CIT rate for all countries in the sample. Column 2 adds the top PIT rate to the full sample. Columns 3 and 4 estimate the effects of tax rates for advanced and emerging market and developing economies, respectively. CIT = corporate income tax; FE = fixed effects; PIT = personal income tax; Y = yes.
*$p < .10$; **$p < .05$; ***$p < .01$.

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PUBLICATIONS

Broadening the Gains from Generative AI: The Role of Fiscal Policies

Staff Discussion Note No. SDN/2024/002