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Sustainability principles can address the looming AI tax gap

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JEL codes: H21; H23; P43; O30

Key words: Optimal Taxation; Environmental Taxes; Public Economics; Technological Change

Sustainability principles can address the looming AI tax gap

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Abstract

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1 Introduction

Epitomized by ChatGPT, artificial intelligence (AI) now shapes every dimension of sustainability, including climate (Kaack et al., 2022), health (Paul et al., 2021), inequality and labor markets (Acemoglu & Restrepo, 2018), water and energy (de Vries-Gao, 2026; Ürge Vorsatz & Creutzig, 2026), existential risks to humanity (Bengio et al., 2024), misinformation and risks to democracy (Schroeder et al., 2026), and overall planetary stability in the Anthropocene (Creutzig et al., 2022). Yet one critical dimension receives insufficient attention: the implications of AI technologies for national and international tax systems.

We argue that AI-driven shifts in factor shares, combined with lower effective taxation of capital relative to labour, pose a material threat to fiscal capacity, public goods provision, and progress toward the SDGs—and that AI taxation should therefore be treated as a core sustainability governance problem, not just a labour market or energy challenge. In this view, AI presents both a systemic fiscal shock and a challenge to the ability of nations to generate revenue. Existing international tax reforms are insufficient once value creation shifts toward AI-intensive capital, requiring a menu of AI-specific tax measures that could restore fiscal capacity while advancing sustainability objectives.

Tax system design intersects with the Sustainable Development Goals (SDGs) in several ways (Figure 1). First, taxes finance scientific research and public investments critical to achieving Goals on water and

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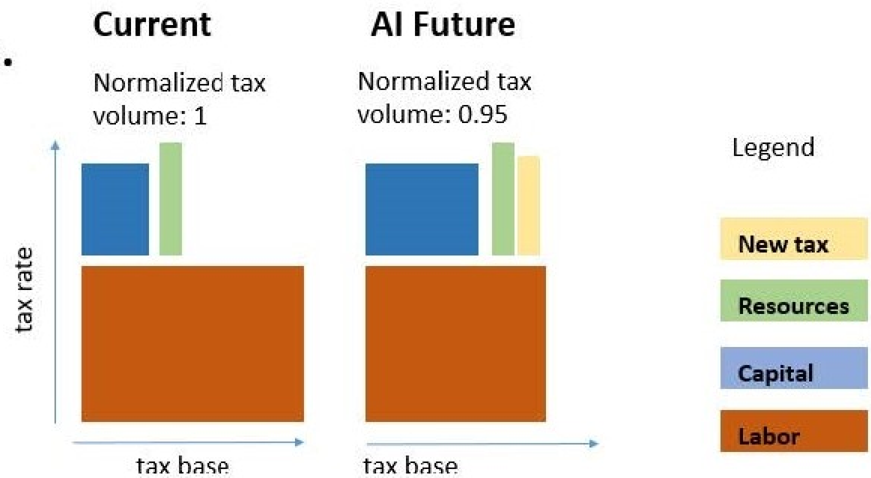
sanitation, energy, infrastructure, and cities. Even debt-funded investments are merely claims against future tax receipts. Second, Pigouvian taxes correct inefficient market failures and incentivize behaviour change, for instance around pollution and waste, with implications for climate and life on land and below water. Third, taxes enable redistribution, directly contributing to poverty reduction, food security, education, and health. Fourth, against a backdrop of automation and potential job displacement, tax system design could play an important role in promoting decent work and economic growth (Acemoglu et al., 2023). Finally, the political economy of taxation reveals that while governance quality and tax revenues are positively correlated, it is the design rather than the overall level of taxation that matters most for overall growth and development (Besley & Persson, 2009; Mirrlees et al., 2011).

a.

Purpose of taxation	Role of AI	Affected SDGs
A. Revenue generation	May shift tax burden and reduce overall revenue	All SDGs (via public finance)
B. Pigouvian efficiency	Externalities of AI remain unaddressed in current tax regime	SDG 13 (and others)
C. Redistribution	May increase inequality via labor market effects	SDG 10
D. Decent work	AI, in particular in the current tax regime, delimits options for decent work	SDG 8
E. Quality of governance	Political economy shifts tax systems towards favoring the ultra rich, creating imbalance and stress in political systems	SDG 16

b.



c.

Compensatory tax	Effect on tax purpose and SDGs
Compute	A. revenue and B. generic externalities of compute power of AI, in particular existential risks
Energy and resources	A. revenue and B. carbon and other resource use externalities and pollution
Data	A. revenue and C.D.E. compensating user data providers, counterfactually prefering decent work, and stabilizing the political economy of the tax system

Figure 1: Rationale for modernising tax systems in response to the rise in AI. a. AI taxation is motivated by five different reasons – revenue generation, Pigouvian efficiency, redistribution, decent work, and quality of governance. **b.** If taxation structure stays constant whilst value generated by labor shifts to capital (AI machines), global tax revenue could fall; governments would lose the ability for future-oriented investments (e.g., in SDGs). **c.** Three different input factors of AI (compute, energy, data) could be taxed to compensate for lost tax revenue

AI also generates environmental and social externalities, suggesting scope for efficiency-enhancing Pigouvian taxation. Firstly, AI is resource intensive. Global electricity demand from data centres is expected to more than double by 2030 to nearly 950 terawatt-hours (TWh) - slightly more than Japan's current consumption (Ürge Vorsatz & Creutzig, 2026). While some AI applications may lead to more efficient energy use and reduced emissions, others might increase environmental degradation, through Jevons' Paradox (sometimes called rebound or scaling effects) (Creutzig et al., 2022). Thirdly, AI systems also raise distributional concerns: they concentrate economic returns on owners of capital and algorithms, rely heavily on uncompensated user data, and may displace workers who cannot readily redeploy. Optimal tax policy may change depending on where economies are in transition: taxes on robots and AI may be needed to compensate displaced workers who cannot reasonably redeploy, but may not be optimal once these workers retire (Guerreiro et al., 2022).

We focus on the revenue implications of AI and because they affect all other dimensions of tax system design: redistribution, financing green transitions, and government provision of public goods. Within countries, labour-augmenting AI could raise the marginal productivity, wages, and income tax contributions of some labour, while labour-displacing AI risks job losses, wage compression, 'hollowing-out the middle' whereby previously high-productivity workers redeploy in lower productivity roles, resulting in declining income tax receipts (Brollo et al., 2024). The available evidence suggests that displacement currently dominates augmentation, but that institutions including tax system design are key policy levers (Acemoglu et al., 2023; Bastani & Waldenström, 2024).

2 Political Economy of AI Taxation

Between countries, the concentration of AI innovation within a small number of firms (and even individuals) could exacerbate long-standing concerns around base erosion and profits shifting (BEPS) already observed with big tech firms. As AI shifts value creation away from labour and towards algorithms and machines (capital), a growing share of value-added accrues to owners of AI-intensive assets. This capital is concentrated in a small number of countries and typically faces lower effective tax rates than labour. The result is a shrinking tax base in many jurisdictions, undermining the fiscal foundations on which public goods such as the SDGs depend. Without proactive tax system design, the resulting economic shift could have significant consequences for social stability, state versus private power-including the ability to govern AI itself - and wider sustainability outcomes.

From a political economy perspective, AI affects tax-system design by creating three asymmetries between AI-intensive firms and the state (Figure 2). These include asymmetries in expertise and information, in the geographic location of value creation versus tax presence, and in political independence and power (e.g., lobbying and regulatory capture). AI-intensive firms generate value through intangible assets—data, algorithms, models, and knowledge capital—that are difficult to observe, measure, and value using conventional accounting and tax tools. Tax authorities face substantial information disadvantages in identifying where value is created, how it scales with compute and data, and how it translates into taxable income. Second, AI technologies increasingly decouple value creation from geographic location, meaning profits can be booked in low-tax jurisdictions independent of the location of users, data collection, compute or deployment. Recent, hard-fought global tax reforms including digital services taxes and the global minimum corporation tax only partially mitigate these concerns. Finally, AI intensifies political asymmetries between a small number of highly concentrated firms and public authorities. Large AI firms possess significant lobbying capacity, legal resources, and agenda-setting power, enabling them to influence the design, timing, and scope of tax reforms. These dynamics are amplified by geopolitical competition, where governments may hesitate to impose taxes perceived to disadvantage "national champions" or weaken strategic positioning in an AI arms race. Regulatory capture and policy delay thus become endogenous risks, further constraining governments' ability to tax AI-intensive activity effectively.

Taken together, these asymmetries imply that the fiscal challenges posed by AI are not simply a matter of adjusting tax rates, but of enhancing state capacity to observe, value, and tax new forms of economic activity. While political economy research on tax, development, and state capacity has focused largely on low-income jurisdictions (Besley & Persson, 2009), similar asymmetries now undermine state capacity even in high-income economies with otherwise strong tax administrations. As AI-driven value creation becomes more concentrated, more mobile, and less tied to labour income, traditional tax bases erode. Effective AI taxation therefore requires tax bases that are difficult to relocate, straightforward to observe, and aligned with the loci of value creation and externalities. These constraints narrow the set of feasible policy instruments and motivate a focus on taxing AI hardware, energy use, and data flows.

International taxation of AI applications and use that is transparent, fair, and administratively feasible will counteract fiscal risks. Beyond addressing specific externalities such as water and energy use, the primary purpose of AI taxation is to restore fiscal capacity to finance public goods—education, health systems, and infrastructure—that underpin economic activity, including that of AI-intensive firms themselves. By rebalancing the contribution of labour and AI-driven capital to public revenues, such taxation can help reduce power asymmetries between a small number of private actors and local and national governments. Revenues may also be used to address related imbalances, including compensating data providers, financing safeguards against systemic AI risks, supporting displaced workers, and investing in sustainable digital and physical infrastructure.

3 Global tax imbalance

Across the OECD, tax-to-GDP ratios averaged 34.1% in 2024, compared to roughly 17% globally, underlining both large cross-country differences in tax capacity and the historical expansion of fiscal systems as economies develop (OECD, 2025b). A defining feature of this evolution is the rise of income taxation: whose share of total revenues has grown from around 5% in 1900 to roughly 50% today (Besley & Persson, 2009). This growing reliance on personal income taxes means that labour-saving AI is not just an employment issue, but a fiscal one. This is exacerbated by the fact that effective tax rates on corporate and labour income diverge sharply: in 2024, the effective average corporate income tax rate across 104 jurisdictions was 20.5% (OECD, 2025a), compared with an average labour tax wedge of 34.9% for a single worker on the average wage in OECD economies (OECD, 2025c).

Governments‘ policy responses face a triple challenge: enabling AI-driven growth, maintaining revenue sufficiency, and building the fiscal capacity to tax AI-intensive activity. The first obstacle is technical feasibility: tax authorities must be able to detect taxable events and enforce compliance in business models built on data, algorithms and intangible assets. The next are political and institutional. AI-intensive firms possess significant lobbying power, while effective taxation often requires coordination across jurisdictions to limit tax competition and regulatory arbitrage. Combined, these constraints reinforce the asymmetries outlined above and limit the efficacy of unilateral, marginal adjustments to existing tax systems.

These tensions are already visible in the taxation of multinational enterprises. Globalisation and the rise of intangible assets often decouple the location of reported profits from that of underlying economic activity, enabling firms to shift profits to low-tax jurisdictions. Recent estimates suggest that around 36% of multinational profits are shifted to tax havens, with US multinationals shifting roughly twice as much as other firms relative to their foreign earnings (Tørsløv et al., 2023). Globally, this translates into revenue losses of around 4-10% of corporate income taxes, or US $100–240 billion annually (OECD, 2016), with particularly large impacts in developing economies, where base erosion and profit shifting losses average around 1.57% of GDP, compared with 0.57% in advanced economies (Crivelli et al., 2016).

To recapture part of this lost revenue, several countries - including France, the United Kingdom, Italy, Spain, Austria, Turkey, India and Kenya - introduced digital services taxes (DSTs). These typically impose levies of 2–7.5% of gross turnover from activities such as online advertising, digital intermediation and monetisation of user data, sourced to the location of users, rather than the parent company's tax residence. By taxing turnover in the market jurisdiction rather than net profit, DSTs are designed to "look through" profit-shifting arrangements. Yet these measures have themselves become a site of international friction. The United States has formally determined that several DST regimes are 'discriminatory' and 'burden or restrict U.S. commerce', and has announced (and in some cases suspended) retaliatory tariffs of up to 25% on affected countries' exports (Noonan & Plekhanova, 2021).

Box 1. Principles of tax system design Governments levy taxes for two reasons: raising revenue and changing behaviour. Behavioural (Pigouvian) taxes entail an inherent trade-off: the more successfully they change behaviour, the less revenue they raise. If carbon taxes drive emissions to zero, they generate no revenue. In contrast, revenue raising taxes are most effective when imposed on 'price inelastic' goods and services - ones that cannot be easily avoided to minimise avertive behaviour, distortions, and economic inefficiencies. Most people need to generate an income, so income taxes are hard to avoid. However, some people can change behaviour to reduce income tax liabilities, for instance by receiving dividends rather than salary (which are taxed at a lower rate), or reducing their working hours. Good tax design seeks to minimise these distortions.

We note there is no optimal tax share of GDP; rich countries exist with high (France, 45%) and low (Singapore 14%) tax ratios. So whilst the overall size of the state is a political choice, the principles of good tax system design require fairness, transparency, compliance (including low enforcement costs), and low recovery costs (Mirrlees et al., 2011). Good fiscal systems evolve with economies to accommodate the rise and fall of key sectors, demographic changes, shifting public tastes and priorities (e.g., with respect to inequality and redistribution), or new geopolitical realities (as Russia's invasion of Ukraine has stimulated public expenditure on defence in Europe). AI could stimulate a sufficiently large economic transformation to require a redesign of tax systems. If value creation shifts from labour to machines, tax receipts could fall, constraining funding for public goods and sustainable development. If AI improves public sector productivity, it may even be possible to deliver the current provision of public goods with lower revenue.

4 The taxation base of AI

We see three feasible avenues to address potential revenue shortfall and expand the AI tax base: taxing AI hardware (compute), taxing data centre energy use, and taxing data flows (Figure 1c).

Low / Medium / High Capacity to address asymmetry	Compute (AI hardware)	Energy use & local externalities	Data & data flows
Expertise & Information	• Observable • Quantifiable • Excludable	• Metered inputs • Existing regulatory infrastructure	• Valuation and attribution remain difficult
Legal & Jurisdictional	• Bypasses profit shifting but concentrates revenue	• Territorial • Source-based • Hard to arbitrage	• Potentially strong with coordination
Political Power (lobbying & regulatory capture)	• Concentrated supply chains but geopolitical resistance	• Pigouvian framing • Local legitimacy	• High lobbying resistance • Coordination-intensive

Figure 2: Political economy asymmetries in taxing artificial intelligence. Addressing local energy and resource related externalities appears relatively feasible in terms of political economy, while data flow taxation requires better access to information and a high degree of international coordination.

First, several properties of AI hardware (compute) make it a promising intervention point for governance and taxation. Compute is highly detectable and quantifiable: AI systems are highly resource-intensive and require substantial infrastructure and energy – some AI supercomputers consume up to dozens of megawatts of power, equivalent to tens of thousands of U.S. households – making them visible and therefore easier to monitor and regulate (Sastry et al., 2024). Quantifiability means that the computational power of hardware can be easily measured and verified through specific metrics like operations per second, which simplifies regulatory oversight. Highly concentrated supply chains mean compute is also excludable: access to chips can be restricted more easily than intangible inputs such as data or algorithms, reducing administrative and enforcement costs for authorities. An international AI chip register would be instrumental in tracking and managing the flow and usage of these chips.

International governance of hardware has so far been focussed on regulatory oversight, primarily to reduce systematic risks (Sastry et al., 2024). But the same properties that make compute governable also make it taxable – at the point of production, export, or deployment, each with its own set of trade-offs. The global AI chip supply chain is heavily concentrated within three key jurisdictions—Taiwan, the US, and the Netherlands. NVIDIA, the dominant AI chip manufacturer, designs its GPUs in the United States, but relies on Taiwan Semiconductor Manufacturing Company (TSMC) for fabrication. The Netherlands hosts ASML, the exclusive supplier of extreme ultraviolet (EUV) lithography machines essential for manufacturing cutting-edge chips. This makes taxation at the point of production or export administratively straightforward, but concentrates revenue in a small number of jurisdictions.

The US and Netherlands could enforce an AI chip export tax, requiring companies like NVIDIA and ASML to collect levies when selling advanced compute hardware. For effective coordination, the EU and US would need to harmonize licensing policies and export tax rates to prevent regulatory arbitrage. China, as a major AI consumer, would be pressured to accept higher chip prices or develop domestic alternatives. Alternatively, compute can be taxed at the place of deployment, predominantly in countries like the USA where large-scale AI models are trained and operated. This could involve a tax on data centers based on their total compute capacity or on specific high-compute activities such as the training of large AI models. Taxing data centers would lead to more equal revenue sharing across countries, but requires greater international coordination as unilateral action would increase the possibility of tax arbitrage if some countries opt out.

Second, AI taxation could target environmental and local public externalities. While global carbon externalities are best addressed through carbon pricing, AI infrastructure also generates significant local impacts, including noise pollution, water extraction, and electricity grid congestion (whereby locally energy bills rise due to high additional load from data centers). Taxing these local externalities could internalise environmental costs whilst providing stable revenue, even where national tax authorities do not impose carbon taxes. Local pollution taxes could additionally make up for revenue shortfalls through the energy transition, for instance as fuel duties erode with electrification. It would also incentivize the development of more efficient and less polluting AI models (which clearly is possible, as demonstrated by DeepSeek). Gradually increasing tax rates for data centers that fail to improve energy efficiency over time would provide dynamic incentives to reduce externalities while allowing a transition period for technological adaptation.

Unlike compute, AI-related energy and water use are geographically dispersed, with major data center hubs in the US, China, and Europe, but also emerging in India, Singapore, the Middle East, and Northern Europe (e.g., Norway and Iceland due to cheap hydroelectric power). Compared to compute taxes, targeting local externalities would create a more geographically distributed tax base and allow jurisdictions to align taxation with local environmental and energy infrastructure constraints, but would come at the expense of greater heterogeneity (and potential for race-to-the-bottom tax competition).

Pigouvian taxes already provide some precedent. For instance, the EU already applies its emission trading scheme (ETS) capturing CO_2 emissions embedded in AI-related energy use. The US, lacking a national carbon tax, could introduce federal energy levies on high-consumption AI infrastructure in alignment with state-level regulations, such as California's clean energy incentives. China could integrate AI-specific energy levies into its carbon pricing scheme. Countries with excess renewable energy could attract AI firms by offering lower tax rates for green-powered data centers.

Third, some scholars have proposed data itself as a potential source of taxation (Oberson, 2025). Unlike traditional corporate taxes on revenues or profits, a data tax would target the raw material of AI: the vast amounts of data collected by technology companies. Conceptually, this would function like a resource tax, such those levied on fossil fuels or rare earths.

Like many resources, the geopolitics are shaped by the fact that the economic benefits of data accumulation are concentrated in a few jurisdictions, primarily the US and China, where large tech firms profit from AI models trained on global data. The EU, which enforces strong privacy laws (GDPR) but lacks dominant AI firms, has a strong incentive to capture tax receipts on the revenue generated by multi-sided platforms that generate profits without being physically present and capture some of the value extracted from their citizens' data.

Data taxes could be volume-based, where levies are imposed on the amount of data transmitted or stored, or value-based, focusing on market returns to data rather than its sheer volume. Other possibilities include data-border adjustment taxes (modeled after carbon border taxes like the EU's CBAM). Corporations would pay a fee when transferring valuable user-generated data to jurisdictions with lower tax rates, combatting BEPS and tax competition. Tiered taxes could be designed, applying lower rates to privacy-protective AI models that rely on decentralized or anonymized data, and higher rates on firms engaged in mass surveillance or intensive data mining.

Data taxation faces significant challenges. One major issue is defining what constitutes taxable data—whether taxation should be based on bytes transferred, unique data points collected, or the economic value derived from AI models built on data. Second, to the extent that data generates value for firms, for instance through data monetization, targeted advertising, or resale of user data, associated profits would already be captured within the existing tax system. Finally, data taxation would require a potentially unreasonably high degree of international tax coordination, cooperation, and enforcement. Unilateral data taxation could discourage AI investments in some countries, leading to a fragmented digital economy with frequent rerouting and jurisdictional arbitrage. Ultimately, data taxation remains the least developed and faces the greatest hurdles, but could become increasingly important if AI- and data-driven value creation rises as a share of economic activity.

5 Solving the Global Coordination Problem of Taxing AI

Taxing artificial intelligence poses a global coordination challenge, driven by asymmetries - in information, geography and legal jurisdiction, and political power - and by geopolitical competition to secure AI leadership. Effective taxation therefore requires differentiated but complementary action across jurisdictions. Countries with leverage over AI hardware supply chains—most notably the United States, Taiwan, and the Netherlands—are well positioned to tax compute at the point of production or export. Jurisdictions hosting large-scale data centres can implement taxes on energy use and local externalities, aligning AI deployment with domestic environmental and infrastructure constraints. Meanwhile, market jurisdictions with large user bases, such as the European Union, have strong incentives to expand user-based digital services taxation to capture revenue and address base erosion and profit shifting. Together, these approaches illustrate how a coordinated but non-uniform AI tax regime could emerge, with different instruments addressing distinct asymmetries while limiting opportunities for arbitrage.

As AI increases factor productivity and reshapes economic structures, traditional tax bases—particularly labour income—are likely to erode, creating a fiscal shortfall that threatens public goods provision (including publicly funded scientific research) and progress toward the Sustainable Development Goals. AI-specific taxation offers a way to counterbalance this shift. By leveraging existing policy levers—export controls and licensing for compute, environmental taxation for energy use, and user-based digital services taxes for data-related revenues—governments can rebuild fiscal capacity in ways that are both feasible and aligned with sustainability objectives. Treated as a core component of sustainability governance, AI taxation can help ensure that technological progress reinforces rather than undermines inclusive and sustainable development.

6 Appendix

A simple way to capture the fiscal consequences of base shifting is to model taxes as the product of an effective rate and a tax base. Let labour and capital tax revenues be $T_L = \tau_L B_L$ and $T_K = \tau_K B_K$. If AI technologies shift a fraction α of the labour tax base to capital, then $B'_L = (1-\alpha)B_L$ and $B'_K = B_K + \alpha B_L$. The implied change in total revenue is $\Delta T = (\tau_K - \tau_L)\alpha B_L$, which is negative whenever capital is taxed at a lower effective rate than labour. Normalising by total revenue yields $\frac{\Delta T}{T} = \alpha s_L \left(\frac{\tau_K}{\tau_L} - 1\right)$, showing that revenue losses scale with (i) the extent of shifting, (ii) the importance of labour taxes in the revenue mix, and (iii) the effective rate gap between labour and capital.

In the following stylised example, let labour taxes generate 50% of total tax revenue ($s_L = 0.50$), the effective labour tax rate is ($\tau_L = 0.35$), and the effective capital tax rate is ($\tau_K = 0.20$). Holding aggregate economic activity constant and abstracting from behavioural responses, consider a scenario in which a fraction of the labour tax base is reclassified as capital income ($\alpha = 0.10$). Taxing this proportion by 20% (capital) instead of 35% (labor) results into about 2.1% reduction in overall tax revenue, holding aggregate economic activity fixed and abstracting from behavioural responses. Currently, about 5% of overall tax revenue is obtained from energy and resource taxation at an approximate tax rate of 30%. Increase taxation of energy and resources to about 50% could compensate for the loss resulting from AI related tax base shift.

Cross-country differences in how taxes are classified, where they are levied, effective tax rates on capital versus labour income, and exclusions, allowances, and deductions can complicate direct comparisons (Hourani et al., 2023). Following convention, we define:

$$\text{Labour tax share} = \frac{\text{PIT (labour)} + \text{SSC} + \text{payroll}}{\text{total tax}} \tag{1}$$

$$\text{Capital tax share} = \frac{\text{CIT} + \text{PIT (capital)} + \text{property}}{\text{total tax}} \tag{2}$$

where PIT refers to personal income tax, SSC to social security contributions (e.g. national insurance), and CIT is corporate income tax. Plugging in values for tax shares and effective average tax rates dervied from (OECD, 2025b) we find that a 10% shift in value-added from labour to capital could reduce tax revenue by 1.8 - 4% across the OECD.

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Competing interests

The authors declare no competing interests.

AI Declaration

ChatGPT was used to help converting from word to Overleaf and choosing colours for Figure 2.

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