the budget lab

How potential AI futures would play out in the current tax system

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Key Takeaways

1	It is widely expected that AI-induced economic growth would make federal debt more sustainable, in part through increased tax revenue, but the way such growth accrues to capital versus labor income may mitigate the revenue gains.
2	We project that by 2030, in a rapid AI growth scenario (3.3 percent annualized GDP growth and a growing capital share), federal revenues could grow by up to $216 billion, a 3.3 percent increase on top of CBO's 2026 baseline.
3	However, higher GDP growth due to AI could skew away from labor. We estimate that—in the rapid growth scenario—total revenue gains from AI would be roughly twice as large if we held the capital and labor shares fixed at their 2026 levels.
4	This gap exists because the US taxes capital income at a lower rate than labor income, and because large swaths of capital income (unrealized gains, retirement benefits, etc.) are excluded from the tax base.
5	There remains great uncertainty about the fiscal implications of AI, but AI should not be expected to solve fiscal sustainability problems on its own, in part because it will likely not raise revenues as much as expected.

The introduction and adoption of powerful new AI models are widely expected to have substantial economic effects, but their implications for the fiscal outlook of the United States are unclear. On the one hand, faster productivity growth would generate more tax revenue, all else equal. On the other hand, our current tax system may not be structured to efficiently collect revenue from the economic activity produced by AI. Economists have focused on two key dimensions that could influence our ability to access the gains from AI: the accrual of gains to the owners of capital (rather than workers) (Drozd and Tavares 2024), and the uncertain effects of AI on the distribution of labor income (Jones 2026). Both academic researchers and government bodies like the Congressional Budget Office have begun to consider what this might mean for both the immediate and long-run outlook of the fiscal system (Korinek and Lockwood 2026).

In this report, we quantify how the current US federal tax system could collect revenue from AI-induced economic growth. We build upon existing TBL infrastructure, namely our tax microsimulation and macro models, to estimate the effect of AI-driven shocks on federal revenue and the distribution of pre- and post-tax income.[1]

We model a variety of scenarios that depend on how large the economic growth boom is, how the extra growth is distributed between capital and labor, and what the AI shock means for inequality in labor income. Other considerations are also important for understanding overall revenue impacts, but we begin with these first-order channels through which revenues could be affected. Considering them together—a task made much simpler with the scenario forecasts from a survey by Karger et al. (2026)—is important because of the offsetting effects that different aspects of an AI shock are likely to have.

In our scenarios, total revenue impacts are usually positive, reflecting the dominant influence of additional economic growth and the relatively muted reduction in labor share in the Karger et al. (2026) forecasts. We find that *if* rapid adoption of AI redistributes income from labor to capital, this would partially offset the additional tax revenues from faster growth. This is driven predominantly by the design of capital taxation, which both exempts large swaths of capital income from taxation (e.g., unrealized gains and retirement income) and applies lower rates to taxable capital income. Revenue effects would also depend on exactly who gains and/or loses labor income in the wake of AI.

We should note that this modeling does not include effects of AI on the spending side (except for outlays that are part of the tax code, like the Child Tax Credit). Previous Budget Lab analysis includes back-of-the-envelope, stylized calculations of increased spending to support workers in a post-AI labor market. That type of increased spending would offset some of the revenue gains we model, and in reality any effects on spending would occur in subtle ways through specific government programs.[2] AI could also matter for tax administration, affecting the ease with which taxpayers avoid taxation and the effectiveness of federal efforts to enforce tax compliance.[3] However, we leave these considerations for future analysis, as they are inherently more difficult to assess in the early days of AI adoption.

The future could play out differently, but the scenario modeling we provide is helpful nonetheless: each scenario constitutes an internally consistent quantitative narrative of how tax revenues evolve in response to an AI shock. Together, those scenarios help us understand how economic shifts from AI are likely to filter through the tax system and represent the first step in building modeling infrastructure that will allow TBL to evaluate future AI scenarios, economic assumptions related to capital taxation, and even potential paths for tax reform.

Projected effects of AI

In this report, we implement our AI scenarios via three interrelated mechanisms: the effect of AI on GDP growth, the share of economic output accruing to capital versus labor, and the distribution of labor income.

The most direct potential economic impact of AI is on productivity and, consequently, on economic growth. All else equal, rising output can be expected to raise revenues (in dollar terms, though not as a share of output).[4] Our quantitative analysis considers three scenarios for economic growth—Slow (2.0%), Moderate (2.6%), and Rapid (3.3%)—each drawn from surveys by Karger et al. (2026). We apply this economic growth to observed levels of taxable income in our data, producing an excess amount of income that is subject to taxation.[5]

Another widely discussed effect that AI might have is on the share of economic output accruing to capital versus labor. The labor share of national income has already fallen to some degree in recent decades, but labor income still makes up slightly more than half of national income. Because capital is typically taxed more lightly than labor, an income shift away from labor and towards capital will tend to reduce revenues. Again using Karger et al. (2026) forecasts, we assume the labor share would be 55.0%, 53.8%, or 51.3% in 2030 for the Slow, Moderate, or Rapid adoption scenarios, respectively.

Some of these forecasts for real GDP growth are unusual from an historical perspective. The Rapid scenario is the most optimistic: the 3.3% real GDP growth rate it assumes has rarely been reached on a five-year average basis since 1990, as shown in Appendix Figure 1. Real growth has more commonly exceeded the Slow and Moderate rates of 2.0% and 2.6%, respectively. However, the slow forecasted pace of labor force growth means that *productivity* growth would need to be commensurately larger to reach any of the Karger et al. (2026) scenario rates of GDP growth. Similarly, the forecasts for the labor share deviate from historical norms. Appendix Figure 2 shows that the assumed levels of nonfarm business labor share are lower in the Moderate and Rapid scenarios than has ever been the case in postwar U.S. history. However, the measured labor share has already declined markedly since 2000 and now stands at 53.7% in the first quarter of 2026, less than 3 percentage points above the Rapid scenario forecast of 51.3%.

The final factor we consider is that of a shift in the distribution of labor income. It is widely believed that the adoption of AI will affect inequality, though there is less agreement about the sign or magnitude of the effect. AI could either compress the distribution of labor income—if, say, LLMs make it easier for non-experts to access expert knowledge and skills—or expand it, if adoption of AI tools disproportionately augments the productivity of those with more education. In the absence of any compelling evidence or survey expectations about how AI will affect inequality, we widen the range of possibilities in our modeling to include negative, zero, and positive effects, defined to be proportional to the size of the output shock: for example, the Rapid adoption scenario features the most economic growth and the largest shift in inequality.[6]

The implications of these key scenario assumptions are described in Table 1. Having stipulated (based on Karger et al. 2026) that GDP would grow at a particular rate from 2026–30, and that the labor share would fall to a given level by 2030, we back out the implied cumulative growth rates (in excess of CBO baseline growth) of GDP, capital income, and labor income.

TABLE 1

Key Parameters

	AI Adoption Scenarios via Karger et al. (2026)		
	Slow (S)	**Moderate** (M)	**Rapid** (R)
AI-adoption inputs *(5-year horizon, 2025-2030)*			
Annual GDP growth under AI	2.0%	2.6%	3.3%
2030 capital share	45.0%	46.2%	48.7%
2030 labor share	55.0%	53.8%	51.3%
Derived cumulative growth *Cumulative over the 5-year horizon, above the CBO baseline path.*			
GDP	0.59%	3.58%	7.17%
Capital	1.72%	7.54%	17.28%
Labor	-0.32%	0.41%	-0.94%
Labor-income inequality parameter *Compressive < 1, Expansive > 1*			
Compressive	0.994	0.964	0.928
Proportional	1.000	1.000	1.000
Expansive	1.006	1.036	1.072

Source: Karger, Buehler, Cox, Saint-Jacques, and Bjorkegren (2026), CBO (2025), and Budget Lab

Data Image

Scenario results

Putting all these pieces together, we now show estimates of revenue responses under the scenarios described above.[7]

Effect of AI growth on federal revenue

Figure 1 shows the overall revenue effects across scenarios. In the Slow variant, federal revenues in 2030 barely change, the result of a nearly identical path when compared to the baseline level of economic growth. In the Moderate scenario, we see revenues are higher in 2030 by between $85 and $127 billion, depending on how labor income inequality changes. (The "Compressive" assumption is that labor income inequality declines; the "Expansive" assumption is that it increases.) Finally, we see the largest revenue gains in the Rapid growth scenario; a maximum of $216 billion with Rapid growth and rising labor income inequality, or an increase in federal revenues of 3.3 percent.[8]

FIGURE 1

Tax revenue is higher when AI adoption is faster and when inequality rises

Change in federal revenue, including corporate tax wedge, FY 2030, Billions USD

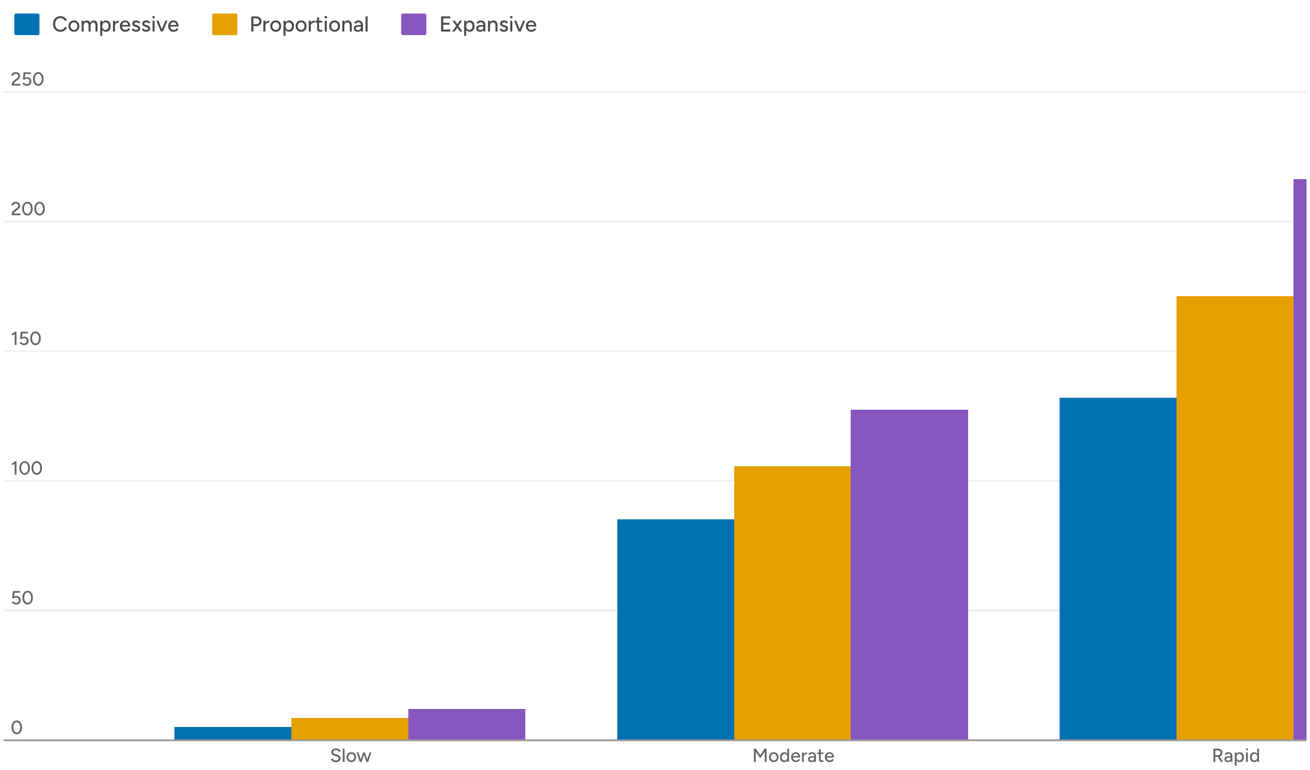

Figure 2 shows how total revenues from corporate income tax, capital taxes, and labor taxes change in each scenario. Moving from the Slow to Moderate to Rapid scenarios, productivity growth and capital share both rise, causing revenue from corporate income tax (dark blue) and capital taxes (orange) to increase as well. In the Rapid-Expansive scenario, the collective increase in those tax revenues amounts to about $216 billion more annually than in the status quo.

More complicated is the effect of AI growth on the revenue from labor taxation across scenarios. Fundamentally, there are two forces at work: a) the degree to which the labor share falls relative to the output increase and b) the change in labor income inequality. If the labor share falls sufficiently relative to GDP growth—as is the case in the Slow and Rapid scenarios—then we estimate there will be a cumulative reduction in labor income relative to the CBO baseline. In those two scenarios, labor income shrinks by between 0.3 and 1.0 percentage points and tax revenue from labor income declines (in most cases). On the other hand, tax revenue from labor income tends to increase in the Moderate scenario because the projected labor share decline is relatively small. Within any of the Slow, Moderate, or Rapid scenarios, labor tax revenue is rising in the amount of labor income inequality, due to the progressive nature of the income tax system. These two forces can move either in the same direction or can oppose each other, depending on the mix of assumptions.

Figure 3 provides a different perspective, decomposing revenue effects by tax instruments, allowing us to observe how payroll and individual income tax receipts vary across AI scenarios, along with corporate tax and tax credit outlays.[9] Payroll and individual income tax revenues change in very different ways across the scenarios. As inequality rises (left to right within a cluster of bars), revenue from the income tax rises, reflecting the progressivity of that tax schedule. In sharp contrast, payroll tax revenue declines as one moves left to right within a cluster of bars. When inequality is higher, more labor income exceeds the Social Security earnings cap and is consequently subject to a much lower tax rate.

Simulating corporate and capital tax receipts requires several additional assumptions, described in the next section and appendix. One of them is that we assume that the additional capital income, generated by the AI shock, is realized at the same rate as capital income at baseline. We make this assumption because our estimate of the excess flow of capital income is based on the observed (realized) capital income in our tax data that grows as specified in our scenarios.

Capital income and growth

Figures 1, 2, and 3 showed only receipts themselves, and not the underlying income flows that are subject to tax. This misses some useful context for the revenue implications: how much of new income is being captured as tax revenue? The most important qualitative answer to this question is that output growth skewed towards capital will tend to lower the share of gross income that is collected as tax revenue. Figure 4 provides a quantitative answer, showing changes in gross income (horizontal axis) along with the revenue changes from Figure 3 (vertical axis).[10]

We note that while revenue grows with the size of the GDP shock, the rate of that growth is higher when labor income is distributed more unequally. In the Rapid scenario, the average tax rate (with gross factor-income as the denominator) varies from 21% (with falling inequality) to 34% (with rising inequality).[11]

Guided by survey respondents' expectations about how the labor share will fall, our AI scenarios imply that excess economic growth skews heavily towards capital and away from labor. This has a pronounced effect on our revenue calculations, as shown in Figure 5. In the most extreme case (with relatively slow GDP growth and a reduction in labor income inequality), the revenue increase above baseline is 82% lower than it would have been if the labor share and distribution had not changed. In every scenario variant, total revenues are lower than they would be had we assumed that the labor share remained constant, and excess economic growth was more balanced between labor and capital.

The stark difference in these revenue projections is driven by two factors. First, capital income faces a much lower average statutory tax rate than labor. This factor is explicit in our tax simulations. Second, implicit in our model is the fact that many forms of capital income are not subject to taxation at all: this includes unrealized gains, preferential treatment for retirement income, and other factors like the holding of equities by non-US citizens.

The distribution of income gains and additional revenues

Our AI scenarios make specific assumptions about how labor income inequality evolves. They also make assumptions about how the capital share rises, which has implications for overall income inequality. It is helpful to understand the implications of these assumptions for inequality as well as the distributional breakdown of changes in tax burden.

Figure 6 shows how overall inequality (including both capital and labor income) shifts in each AI scenario. Interestingly, inequality is only moderately increased by more-rapid AI adoption when labor income is assumed to accrue proportionally.[12] More important in our simulations is the assumption about how labor income inequality changes along with an AI shock: overall inequality rises when labor inequality does. However, this comparison depends entirely on what we assume about the magnitude of the labor inequality change, for which there is very little guidance in the research literature.

With the mix of income and tax revenue changes in each scenario, it is not immediately obvious how average tax rates might change across the distribution of taxpayers. Figure 7 shows the percentage point change in average tax rate for the Moderate scenario, assuming a proportional shock to the distribution of labor income. Average tax rates grow modestly for almost all deciles, reflecting the accumulation of income in higher tax brackets. We also see that this effect tapers off at the top of the income distribution due to the income mix for tax filters in the top decile being especially capital heavy.

The analysis above is focused on the revenue and distributional implications of different AI shocks. This leaves unanswered some important questions about the overall fiscal picture that depend on how net interest payments and non-interest outlays respond to the AI shock. In Appendix Figure 4, we show how debt-to-GDP shares in 2030 deviate from baseline in each AI scenario.[13] The most important driver of those deviations is the assumed output growth rate through 2030. However, we do not attempt to model how federal expenditures would respond in AI scenarios, which would have important implications for the debt trajectory.[14]

AI holds promise and peril for the fiscal system

Unfortunately, the additional output growth that is often expected from AI—a clear positive for the fiscal picture—is not the only potential impact that matters. Another widely expected consequence of AI adoption is a reduction in the labor share of income. This bias in AI-induced growth reduces the revenue increase one would otherwise expect, given the preferential tax treatment afforded to capital income. Further, any labor inequality effects of AI could increase revenues (in the case of increasing inequality) or reduce them (in the case of decreasing inequality).

Because these channels are of first-order importance for understanding AI effects on tax revenues, our analysis focuses on their roles. Other channels, not considered here, could also turn out to have meaningful revenue implications. One such channel could be labor supply changes, to the extent that they are not effectively captured by our various assumptions about overall economic growth, labor share, and labor inequality. Another factor is the effect of AI on tax avoidance and enforcement, where it is unclear if increased access to these tools will provide more assistance to the IRS or to noncompliant taxpayers.

Some assumptions in our analysis could also be inadequate to the reality of future AI-related changes. For example, a wealthier post-AI world could be one in which taxpayers realize a smaller or larger share of their capital income. AI-generated capital income may also flow disproportionately to certain taxpayers and assets, with consequences for overall tax revenues. And our stylized assumptions about AI effects on labor income inequality include a wide range of possibilities, which further work could aim to narrow. We at The Budget Lab aim to expand our modeling capacity to address these and other analytical challenges. We also plan to update as more information about the effects of AI becomes available.

Appendix

This appendix provides additional details that are helpful for understanding and interpreting the results. For the full details, see the accompanying methodology document. The model is available on GitHub here, but the data used to analyze the scenarios cannot be released publicly.

We begin with the tax-unit level data created for and used by The Budget Lab's tax microsimulation model, based on the 2015 IRS Public Use File, which is aged to the baseline year (2030 in our case) through SSA population weights and the CBO economic forecast. We impute asset values onto these tax units using the Survey of Consumer Finances (SCF) and a random-forest machine-learning approach. Notably, our baseline incorporates the CBO's assessment of the growth effects of AI, which in 2026 were approximately 10 basis points per year on average.

Based on the particular scenario we adjust overall labor and capital income to account for AI effects on the GDP growth path, labor share of income, and distribution of labor income. We then apportion these changes to individual tax returns on the PUF. Using our tax microsimulation model and a simple representation of the corporate income tax, we then obtain revenue and distributional estimates by comparing the data before and after these adjustments.

Below, we show some of the key calculations for implementing the Karger et al. (2026) scenarios. Second, we describe additional economic assumptions not discussed above. Third, we discuss our process for combining these results with our macro modeling capacity to estimate debt-to-GDP ratios. Finally, we present a few additional figures.

Technical details

Table 1 (reproduced below with variable symbols) provides the values for key variables that are implied by our implementation of Karger et al. (2026) economic forecasts. These include the output increase and the decline in labor share. Because survey respondents were asked about three consistent scenarios (Slow, Moderate, and Rapid), we can link the labor share and economic growth changes together. Further, while our calculations for the change in labor income inequality were not directly taken from the Karger et al. (2026) paper, we use their GDP growth projections as inputs to estimate the scale of labor income compression or expansion. The calculations underlying Table 1 values were conducted as follows:

We begin with a CBO baseline level of cumulative GDP growth through 2030 of 9.7%, or 2.2% for 2026 and 1.8% for all following years (G_{CBO}). We also have pre-shock labor (θ_0^L) and capital ($\theta_0^K = 1 - \theta_0^L$) shares of factor income. From the aged PUF, we have a pre-shock distribution of labor income.

For any scenario, we begin by scaling up the cumulative CBO growth rate by the annualized rate (r_{ai}) from Karger et al. (2026).

$$g_Y = \frac{(1+r_{ai})^5}{G_{CBO}} - 1.$$

The growth rates of capital (g_K) and labor (g_L) follow from g_Y and the pre-and post-shock factor income shares of capital and labor; $(\theta_0^K, \theta_1^K, \theta_0^L, \theta_1^L)$:

$$g_K = \frac{\theta_1^K (1+g_Y) - \theta_0^K}{\theta_0^K}, \qquad g_L = \frac{\theta_1^L (1+g_Y) - \theta_0^L}{\theta_0^L}$$

The labor growth rate (g_L) is negative for Slow and Rapid because the labor share (θ_1^L) falls fast enough to outweigh productivity gains over the five-year horizon.

The aggregate capital income flow added by the shock is:

$$Y_1^K = \ Y_0^K \cdot (1 + g_K)$$

where Y_0^K is the baseline level of realized, taxable capital income observed on the PUF. Because we are defining our AI shock as a function of taxable income, we are assuming that the rate of realization of capital income is unchanged by the AI shock. We then apportion Y_1^K to individuals based on their total assets (imputed from the SCF) and within individuals across types of capital income (capital gains, dividends, interest, retirement accounts, etc.) proportional to types of assets (equities, bonds, etc.).

The aggregate labor income flow added by the shock is:

$$Y_1^L = \ Y_0^L \cdot (1 + g_L)$$

The "labor income inequality parameter (λ)" rows govern the within-tax-unit dispersion of the labor shock under the compressive or expanding specifications. For the proportional model, we simply scale up all positive labor income by a single multiplier to target post-shock aggregate labor income (a function of g_L).

For the expansive and compressive scenarios, we re-estimate labor income for tax unit *i* $(Y_{1,i}^L)$ using the following specification:

$$Y_{1,i}^L = \mu_1 + \lambda \cdot \left(\ln Y_{0,i}^L - \mu_0 \right).$$

Where λ is the ratio of the post- to pre-shock standard deviation of $\ln Y_{j,i}^L$ restricting attention to only those tax units with positive labor income. Here, μ_0 is the weighted log-mean of positive baseline labor income and μ_1 is solved so the positive-subset aggregate matches Y_1^L after scaling.

Under the assumption that any shift in distribution will be correlated with the size of the AI shock, we estimate λ as a function of the GDP shock g_Y so that: $\lambda = 1 \pm k \cdot g_Y$, where $1 - k \cdot g_Y$ is compressive and $1 + k \cdot g_Y$ is expansive. The default $k = 1$ is the proportional-to-g_Y mapping.

Economic assumptions and limitations

To calculate the additional revenue in our AI scenarios, we require several assumptions about how additional income flows through the tax system. These relate to how corporate income is taxed and how capital is realized.

First, corporate income tax (CIT) operates upstream of household realizations, so in order to capture the effect of an AI shock on corporate income tax revenue, we need to estimate what growth in C-corporation income is implied by X. We proceed simply by multiplying the change in capital income by the ratio of CBO's baseline level of CIT revenue (R^{CIT}_{CBO}) to baseline (2030 in this case) realized capital income (Y^K_0), implying that the AI CIT delta then scales linearly with X:

$$\Delta R^{CIT} = X \cdot \frac{R^{CIT}_{CBO}}{Y^K_0}$$

This assumes that the effective tax rate on corporate income is constant.

The allocation and taxation of excess capital income poses a few complicated challenges. The most basic question is how that excess income should be distributed across assets. One could reasonably assume that the income accrues only to assets that AI has directly made more productive. However, this approach would run into sharp data limitations, and we choose to distribute excess capital income proportionally across asset types. In doing so, we use the Survey of Consumer Finances data to make allocations across households, proportionally to their asset holdings (some but not all of which are observable in the public-use tax records). Subsequent to this allocation, each household's new income is allocated to income from asset classes that are observable in the tax records: equities, bonds, pass-through equity, and retirement accounts.

Income generated by business passthroughs (S-corporations and partnerships) is a mixture of capital and labor income. We follow Saez and Zucman (2020) by allocating passthrough profits up through the 99.99th percentile of wages in a 25% (capital) – 75% (labor) split; profits above that threshold are allocated 75% (capital) –25% (labor).[15]

Debt-to-GDP

To further explore the fiscal picture, we calculate scenario-specific changes in revenue-to-GDP shares using the approach described above. We then use the Budget Lab's Small Macro Model (BLSMM) to determine what these revenue changes mean for the debt-to-GDP ratio in 2030. To keep things as consistent as possible between the BLSMM and tax models, we simultaneously raise the potential output growth rate assumed in BLSMM until actual GDP growth in 2030 is equal to the rate assumed in the scenario-specific Karger et al. (2026) forecast.[16] Importantly, the BLSMM model assumes CBO's so-called rules of thumb, which dictate how outlays (as a share of GDP) respond to changes in potential output. As discussed in prior Budget Lab analysis, an AI shock could be different than others in the sense that policymakers might want to spend on displaced worker support. If that occurs, outlays would likely rise more than expected by BLSMM, increasing debt relative to our calculations.

Footnotes

1 The model is available via GitHub, and a full methodology document is available here.

2 See CBO (2024) for further discussion of potential revenue and outlay implications.

3 Federal government implementation of AI could improve IRS monitoring and audits, making them cheaper and more effective. But taxpayers could also make use of AI tools to find and exploit avoidance opportunities. In the short run, the relative pace of adoption will likely be a factor that helps determine whether AI makes tax administration more or less effective on net.

4 We chose to implement the Karger et al. (2026) scenarios in terms of GDP growth (in excess of baseline growth) in order to abstract from the offsetting dynamics of productivity increase and labor supply decline. See prior Budget Lab analysis for a different approach that unpacks those two channels. But note that the current analysis is not directly comparable to that prior work, one reason for which is that different elements of the Karger et al. (2026) scenarios are used in each analysis.

5 Alternatively, one could apply the shock to GDP directly and—via some macroeconomic model—have the shock flow into factor income, inclusive of types of capital income not observed on tax returns (e.g. unrealized gains). We adopt our current approach for simplicity but anticipate building a more comprehensive model in future work.

6 This is operationalized as a reduction or increase in the standard deviation of labor income, such that the incremental reduction/increase in each taxpayer's labor income is a constant percent of their existing deviation from the overall mean.

7 Several assumptions about realization, retirement income, the corporate income tax, and other relevant considerations are described in the appendix.

8 CBO's estimate of total FY 2030 revenue was $6,595 billion.

9 Remember that the individual income tax is levied on both labor income (e.g., wages and salaries) and capital income (e.g., dividends, interest, and capital gains). It is also levied on taxable distributions from pensions and IRAs, which we treat as capital income

10 Appendix Figure 3 provides the same analysis as Figure 4, but with a horizontal axis showing pre-tax income.

11 The story is roughly similar when limiting the analysis to income that appears on a tax return, i.e., excluding untaxed interest income and corporate tax, as is clear when comparing Figure 4 and Appendix Figure 1.

12 Part of the reason for this is that excess capital income in our scenarios remains fairly small compared to baseline labor and capital income. A longer-term simulation would yield larger effects on inequality.

13 The baseline used is the Budget Lab's small macro model baseline, which is designed to approximate the most-recent CBO baseline.

14 We use The Budget Lab's small macro model for these calculations. It incorporates CBO's rules of thumb, which imply a non-interest outlay response that may differ substantially from what would actually occur in AI scenarios.

15 Passive profits are uniformly allocated 75% (capital) / 25% (labor).

16 Specifically, we layer the tax simulation's implied decrease in the revenues-to-GDP ratio on the BLSMM revenue baseline. This has little to no effect on GDP growth rate in 2030.