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CAN AI RESTORE FISCAL SUSTAINABILITY IN THE US?

ACCOUNTING FOR AN AI-DRIVEN PRODUCTIVITY SHOCK

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Introduction

It is well-known that the federal budget is on an unsustainable trajectory. The most recent long-term estimates by the Congressional Budget Office (CBO) project the public debt as a share of GDP to reach 175 percent by 2056.[1] While many analysts have expected that a fundamental rebalancing in fiscal policy would ultimately be required, the recent explosion in Artificial Intelligence (AI) investment has prompted newfound optimism that the U.S. may grow its way out of the budget morass. Indeed, prior productivity shocks, namely those in the 1980s and late 1990s, were associated with rising tax revenues and lower annual deficits—although there is no clear picture as to the precise impact of the shocks and the subsequent change in deficits.

The aim of this paper is to scope the potential size of an AI shock on federal budget outcomes accounting for both plausible macroeconomic and demographic developments as well as practical fiscal considerations, including characteristics of the tax code and various spending programs.

Achieving this requires two analytical steps. First, to identify and model the particular channels through which an AI-induced shock impacts the federal budget. Our approach includes the identification of novel channels, such as reduced mortality rates and higher defense spending, as well as conventional channels like higher GDP and an elevated neutral rate of interest (r*). The second step is to estimate the potential size of the impact on macroeconomic variables like productivity, labor force participation, and labor share of national income. Here, our estimates are informed by both historical experience and forward-looking projections on the potential magnitude of this shock.

1 Congressional Budget Office, The Budget and Economic Outlook: 2026 to 2036 (Washington, DC: Congressional Budget Office, January 2026), https://www.cbo.gov/publication/62105.

In meeting this aim, the paper presents results from a newly developed fiscal and macroeconomic model designed to measure the impact of a large-scale productivity shock on the ten-year fiscal outlook. Importantly, this model accounts for dynamics associated with the current AI shock, including changes in the labor force participation rate and subsequent increases in income support spending, reduced mortality rates owing to health advances, shifts in national income between capital and labor, higher interest rates owing to elevated neutral rates of interest, increased defense spending, rising rates of Disability Insurance claiming, changes in Medicare and Medicaid utilization and pricing, and other such factors.

We simulate four representative productivity shocks to estimate potential impacts on the fiscal outlook. One shock is a traditional productivity shock similar to other post-war experiences. Another corresponds to a shock that disproportionately impacts the labor market, shifting the composition of new income and displacing a meaningful share of workers. A third shock corresponds to a health-focused shock where productivity gains are concentrated in the health sector, with attendant reductions in mortality and increased health care efficiency and utilization. A final shock corresponds to a composition of these three scenarios.

The results are straightforward. A large, conventional productivity shock could largely mitigate longstanding fiscal imbalances through expanded tax bases and higher revenue—potentially reducing the annual deficits from about 6 to roughly 2 percent of GDP. However, the idiosyncratic nature of the AI shock may limit these gains, primarily through five channels. One, lower mortality rates lead to a sharply higher retirement-age population, which raises entitlement spending. Two, a shift from higher-taxed labor income to lower-taxed capital income reduces the average tax rate. Three, lower labor force participation

raises enrollment in income support programs. Four, increased investment in AI raises the neutral rate of interest and market interest rates, boosting debt service costs. And finally, an AI arms race could accelerate defense spending as world powers engage in elevated defense spending. Ultimately, these factors contribute to the recapturing of over half the gains associated with a conventional productivity shock.

The remainder of this paper is organized as follows. Section II discusses prior productivity shocks and their impact on the fiscal outlook. Section III presents the methodology and Section IV presents the results. Section V concludes.

Prior Productivity Shocks and the Federal Budget

This section first addresses the historic relationship between productivity shocks and the federal budget, then reviews the specific relationships between productivity shocks and discrete budget channels. It closes with a review of contemporary estimates regarding the size and scope of an AI-driven productivity shock.

A. Historical Productivity Shocks and Fiscal Outcomes

Increases in productivity are not continuous features of modern economies; instead, they are episodic, created by transformative technologies with macroeconomic and fiscal consequences. Gordon's (2016) comprehensive account of the American standard of living establishes this pattern across 150 years of economic history. For example, 1920 to 1970 was an era of particularly strong technological change. During this time, total factor productivity, the best available measure of innovation, grew at nearly triple the rate compared to the periods before and after.[2] Gordon identifies the clustering of what he terms the "Great Inventions": electrification, the internal combustion engine, indoor plumbing, and advances in communications, as the proximate cause of this surge.[3]

The fiscal consequences were substantial and long-lasting. The post-war tax regime, broadened to a mass income tax during World War II, proved durable in part because economic growth enabled the federal government to garner increasing revenues without raising tax rates, financing the expansion of both domestic and foreign programs through the late 1970s in what Brownlee (2004) terms the "Era of Easy Finance."[4] Though not causal, it is worth emphasizing that real federal revenues and outlays increased by approximately 204 and 186 percent, respectively, between 1950 and 1970, compared to only 46 and 70 percent between 2005 and 2025,[5] a period of notably slower productivity growth.

Not all technological changes correspond to immediate measured productivity growth, however, as was seen in the 1980s with the large-scale adoption of computers. Robert Solow famously observed in 1987 that "you can see the computer age everywhere but in the productivity statistics,"[6] and researchers documented the explosion in information technology spending with little corresponding growth in aggregate output. For example, despite real business investment in computer hardware growing at more than 31 percent annually throughout 1974 to 1990, labor productivity in the nonfarm business sector grew at only 1.4 percent per year, lower than in any

2 Robert J. Gordon, "Introduction: The Ascent and Descent of Growth," in The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War (Princeton University Press, 2016), 14, https://doi.org/10.2307/j.ctvc77bwm.4.
3 Ibid., 2.
4 W. Elliot Brownlee and Lee H. Hamilton, Federal Taxation in America: A Short History (Cambridge University Press, 2004), 107–144.
5 U.S. Office of Management and Budget, "Table 1.1—Summary of Receipts, Outlays, and Surpluses or Deficits: 1789–2025," Historical Tables (The White House), accessed April 21, 2026, https://www.whitehouse.gov/omb/information-resources/budget/historical-tables/.
6 Robert Solow, "We'd Better Watch Out," New York Times Book Review 36 (1987).

comparable period through the end of the century.[7] Brynjolfsson and Hitt (1996), analyzing firm-level data from 1987 to 1991, found that despite enormous improvements in computing technology, the benefits of that investment had not materialized in aggregate output statistics.[8] The productivity payoff did eventually arrive, but only after a substantial lag.

The cycle of business investment and subsequent rises in profit illustrate a complicating factor in assessing the revenue implications of productivity shocks, namely that business investment is generally tax deductible—which means that productivity shocks can reduce taxable income in the preliminary period as business spend to expand capacity and before the shock results in higher profits. At the same time, assessing the impact of productivity shocks on federal revenues is complicated by confounding factors, namely changes in tax law and other demographic and economic changes.

These dynamics can be seen in the 1980s. Here, the income tax share of GDP declined from 8.2 percent in fiscal year 1983 to 8.0 percent in fiscal year 1989, a modest shift compared to the dramatic swings that accompanied the productivity surges both before and after.[9] Yet, this was an exceptionally active period in terms of fiscal legislation. A sweeping tax cut in 1981 sharply reduced federal income tax revenues,[10] and it was followed five years later by base-broadening tax reform that helped restore the income tax base.[11] On the spending side, the Reagan-era defense buildup increased nominal defense outlays by nearly 45 percent between 1983 and 1989 while the share of retirement-aged individuals skyrocketed and thus expanded Social Security and Medicare outlays.[12]

A more recent analog from the information technology boom of the late 1990s provides a clearer picture of the causal chain from technology adoption to productivity acceleration to fiscal outcomes. Oliner and Sichel's (2000) growth accounting analysis finds that labor productivity in the nonfarm business sector rose from just over 1.5 percent growth annually during 1991 to 1995 to nearly 2.6 percent growth during 1996 to 1999,[13] with the use and production of information technology together accounting for approximately two-thirds of that roughly one percentage point acceleration.[14]

The revenue consequences of this productivity surge were likely substantial. CBO analysis documents that individual income tax revenues grew 85 percent between fiscal years 1994 and 2000, more than double the 39 percent growth in nominal GDP over the same period, pushing the income tax share of GDP from 7.8 percent to a high of 10.3 percent.[15] Critically, tax legislation explains almost none of this increase: absent any legislative changes, income tax revenues would have risen an estimated 2.7 percentage points as a share of GDP, as opposed to the lower actually observed increase of 2.4 percentage points.[16] In addition, federal outlays grew 22 percent in nominal terms over the time period.[17] The productivity surge of the late 90s cannot solely account for the growth in revenues and outlays of this era, but history shows a clear

7 Stephen D. Oliner and Daniel E. Sichel, "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?" Journal of Economic Perspectives 14, no. 4 (2000): Table 1, 10; Table 2, 13.
8 Erik Brynjolfsson and Lorin Hitt, "Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending," Management Science 42, no. 4 (1996): 541–558.
9 U.S. Office of Management and Budget, "Table 2.3—Receipts by Source as Percentages of GDP: 1934–2030," Historical Tables (The White House), accessed April 21, 2026, https://www.whitehouse.gov/omb/information-resources/budget/historical-tables/.
10 Economic Recovery Tax Act of 1981, Pub. L. No. 97-34, 95 Stat. 172 (1981).
11 Tax Reform Act of 1986, Pub. L. No. 99-514, 100 Stat. 2085 (1986).
12 U.S. Office of Management and Budget, "Table 3.1—Outlays by Superfunction and Function: 1940–2030," Historical Tables (The White House), accessed April 21, 2026, https://www.whitehouse.gov/omb/information-resources/budget/historical-tables/.
13 Oliner and Sichel, "Resurgence of Growth," Table 2, 13.
14 Ibid., Table 5, 19.
15 Kurt Andrew Seibert, "Sources of the Growth and Decline in Individual Income Tax Revenues Since 1994" (Washington, DC: Congressional Budget Office, 2008), 1.
16 Ibid., 2.
17 U.S. Office of Management and Budget, "Table 1.1—Summary of Receipts, Outlays, and Surpluses or Deficits: 1789–2025," Historical Tables (The White House), accessed April 21, 2026, https://www.whitehouse.gov/omb/information-resources/budget/historical-tables/.

correlation between increases in productivity and the federal budget: federal revenues tend to rise as incomes increase, and federal outlays tend to rise as well, albeit through more complex channels tied to mandatory spending, discretionary spending, and debt service costs.

B. Specific Channels through which Productivity Impacts Fiscal Outcomes

Productivity growth tends to translate into higher tax revenues primarily through tax base expansion, with long-run responsiveness close to proportional in most advanced and emerging economies. Cross-country evidence shows that aggregate tax revenues exhibit a long-run buoyancy (i.e., the measure of how taxes respond to economic growth through both automatic and discretionary changes) near unity with respect to economic activity, implying that sustained productivity-driven growth generates commensurate increases in revenue over time, even though short-run responsiveness is weaker and varies across tax instruments.[18] For instance, Belinga et al. (2014) estimate a long-run panel buoyancy for aggregate tax revenues of 1.06 across 34 OECD countries over 1965–2012.[19] Importantly, much of the observed growth in revenues historically reflects both automatic responses of tax bases and discretionary policy changes, such as statutory rate changes, base-broadening reforms, or new program-linked levies,[20] complicating causal attribution of productivity in revenue-growth regressions.

The above literature implies that productivity growth improves fiscal outcomes on the revenue side in a systematic manner, with the strength of the effect shaped by tax structure and the distribution of productivity gains across income sources. For example, the revenue implications of a productivity shock may also depend on its factor bias. A labor-augmenting shock that raises wages would disproportionately expand the personal income and payroll tax bases, which face a combined federal marginal rate of approximately 27.2 percent in 2026; a capital-augmenting shock that raises returns to capital would instead mainly expand tax bases related to capital income, subject to an effective marginal rate of roughly 11.7 percent in 2026.[21] To our knowledge, no empirical literature directly estimates differential revenue buoyancy by type of productivity shock, leaving this an open area for future research.

Productivity growth also affects entitlement spending through distinct channels across programs, with markedly different implications for health and non-health entitlements. In Medicare and Medicaid, higher aggregate productivity does not automatically restrain spending growth because health care delivery remains a relatively labor-intensive sector;[22] health entitlement costs have historically risen faster than GDP, with Medicare and Medicaid costs as a share of GDP increasing from 0.6 and 0.3 percent of GDP in 1970 to 3.9 and 2.2 percent of GDP in 2025, respectively.[23] Thus, one first-order question is the extent to which the productivity shock directly affects the healthcare sector.

On one side, the healthcare sector exhibits substantial misallocation and inefficiency that a productivity shock could reduce: Baicker, Chandra, and Skinner (2012) find no systematic relationship between spending levels and patient survival rates for common serious conditions across more than

18 Antoine Cornevin, Juan Corrales, and Juan Pablo Angel, A Deep Dive into Tax Buoyancy: Comparing Estimation Techniques in a Large Heterogeneous Panel (International Monetary Fund, 2023), 20.

19 Vincent Belinga et al., Tax Buoyancy in OECD Countries (International Monetary Fund, 2014), 11.

20 Christina D. Romer and David H. Romer, "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks," American Economic Review 100, no. 3 (2010): 763

21 Congressional Budget Office, "Tax Parameters and Effective Marginal Tax Rates," tab "2. EMTR on Labor" and "3. EMTR on Capital," February 2026, accessed March 17, 2026, https://www.cbo.gov/data/budget-economic-data#10.

22 William J. Baumol, The Cost Disease: Why Computers Get Cheaper and Health Care Doesn't (Yale University Press, 2012).

23 Congressional Budget Office, "Table 5a: Mandatory Outlays Since 1962, as a Share of GDP," Historical Budget Data, February 2026, https://www.cbo.gov/data/budget-economic-data.

3,800 hospitals.[24] On the other, past promises of productivity improving technologies have failed to generate system level cost savings: Agha (2014) finds that health information technology adoption among Medicare hospitals was associated with a 1.3 percent increase in billed charges, with no evidence of cost savings or improved patient outcomes even five years after adoption.[25] Social Security Old Age and Survivors Insurance (OASI) is also fundamentally linked to mortality, which health-specific productivity shocks may materially impact. We provide a more complete consideration of health productivity shocks below.

By contrast, Social Security Disability Insurance (SSDI) and income support programs are more tightly linked to labor market outcomes. Productivity growth typically, though perhaps not in the case of an AI-shock, leads to stronger labor demand, which reduces disability and means tested benefit participation.[26] Empirical evidence also demonstrates that declining labor demand for lower skilled workers, a negative analog to general productivity growth, drove substantial increases in SSDI rolls, illustrating how labor market conditions directly shape program costs.[27] Means tested programs exhibit similar sensitivity: Ganong and Liebman (2018) find that the majority of the rise in SNAP enrollment between 2007 and 2011 was driven by deteriorating labor market conditions, with unemployment accounting for the largest share of cyclical variation in caseloads.[28] Taken together, the literature suggests that traditional productivity growth improves entitlement sustainability most directly through labor market channels and non-health programs, while its effects on health entitlements depend critically on whether productivity gains occur within the healthcare sector itself rather than solely in the broader economy.

The empirical literature on overall government expenditure and productivity growth provides consistent support for the view that public spending rises with national income. Lamartina and Zaghini (2011) use panel cointegration analysis across 23 OECD countries to find a structural positive correlation between per capita GDP and total government expenditure, with a long-run elasticity above one that declines gradually as economies mature.[29] Their long-run elasticity estimate implies that a 10 percent increase in per capita GDP corresponds to an approximately 10.3 percent increase in total government expenditure. Brückner, Chong, and Gradstein (2012), using oil price shocks as an exogenous source of income variation, confirm a statistically significant positive income elasticity of government spending, suggesting that spending grows with income but less than proportionally.[30] Durevall and Henrekson (2011) find long-run historical evidence for Sweden and the United Kingdom that the income-spending relationship held robustly during the formative period of the modern public sector but exhibits significant structural variation across periods and institutional settings.[31]

While this literature focuses on total government expenditure rather than U.S. discretionary outlays specifically, the underlying mechanism, that rising productivity and income expand the fiscal capacity and political demand for public spending, applies with particular force to discretionary categories: unlike mandatory entitlement spending, discretionary spending is allocated through annual legislative decisions that respond to both

24 Katherine Baicker, Amitabh Chandra, and Jonathan S. Skinner, "Saving Money or Just Saving Lives? Improving the Productivity of US Health Care Spending," Annual Review of Economics 4, no. 1 (2012): 33–56.

25 Leila Agha, "The Effects of Health Information Technology on the Costs and Quality of Medical Care," Journal of Health Economics 34 (2014): 19–30.

26 Congressional Research Service, "Social Security: Economic Growth and the Funding Shortfall," R46479, August 6, 2020, https://www.congress.gov/crs-product/R46479.

27 David H. Autor and Mark G. Duggan, "The Rise in the Disability Rolls and the Decline in Unemployment," Quarterly Journal of Economics 118, no. 1 (2003): 157–206.

28 Peter Ganong and Jeffrey B. Liebman, "The Decline, Rebound, and Further Rise in SNAP Enrollment: Disentangling Business Cycle Fluctuations and Policy Changes," American Economic Journal: Economic Policy 10, no. 4 (2018): 153–76.

29 Serena Lamartina and Andrea Zaghini, "Increasing Public Expenditure: Wagner's Law in OECD Countries," German Economic Review 12, no. 2 (2011): 149–164.

30 Markus Brückner, Alberto Chong, and Mark Gradstein, "Estimating the Permanent Income Elasticity of Government Expenditures: Evidence on Wagner's Law Based on Oil Price Shocks," Journal of Public Economics 96, no. 11–12 (2012): 1025–1035.

31 Dick Durevall and Magnus Henrekson, "The Futile Quest for a Grand Explanation of Long-Run Government Expenditure," Journal of Public Economics 95, no. 7–8 (2011): 708–722.

legislative priorities and available resources. The overall empirical picture characterizes government spending as increasing with income, with the elasticity positive but declining at higher levels of development and with substantial heterogeneity across countries and time periods.

Changes in interest rates can also impact fiscal outcomes outside of changes to primary deficits. Standard growth theory predicts a positive relationship between trend productivity growth and the equilibrium real interest rate: faster productivity growth raises the expected return to investment, shifting the demand for capital and pushing up real rates. Model-based estimates of the natural rate of interest provide some support for this prediction at the macroeconomic level. Research finds that the pronounced decline in estimated natural rates across the United States, Canada, the Euro Area, and the United Kingdom since the 1990s coincided with declining trend GDP growth.[32] This co-movement across economies points to common secular forces, including slowing productivity, as partial explanations for persistently low equilibrium rates.

However, the empirical evidence on the relationship between productivity growth and observed safe real interest rates is more mixed. Long-run historical data for advanced economies do not consistently show higher safe returns during periods of faster productivity or economic growth, and studies find that the long-run correlation between productivity growth and safe real rates is near zero or even negative over the full historical record.[33] The evidence supports the view that trend productivity growth is a structural determinant of the equilibrium interest rate, but it also suggests that this relationship is substantially obscured in realized data by a range of structural forces including demographic shifts, saving dynamics, and rising public debt.[34]

Earlier work on AI and health[35] by two of this paper's authors (Harris and Mehrotra) highlights a class of productivity shocks whose primary fiscal transmission runs not through aggregate output or income, but through age-specific mortality, morbidity, and healthcare utilization, channels that directly affect mandatory spending on Social Security, Medicare, Medicaid, and related income-security programs. AI-driven improvements in health may expand or reduce entitlement outlays even in the presence of faster economic growth through changes to mortality, utilization rates, and prices.

AI's impact on health care utilization operates through competing channels that make the net fiscal effect difficult to predict. On the cost-reducing side, AI tools improve diagnostic speed and accuracy, enabling earlier intervention and reducing the need for more intensive downstream treatment. AI-assisted systems have demonstrated significant reductions in diagnosis time: one neural network reduced time-to-diagnosis for intracranial hemorrhage by 96 percent through rapid CT scan analysis.[36] Machine learning models that predict patient readmission risk offer further potential to reduce costly repeat hospitalizations, particularly among older patients.[37] Perhaps the most direct analog for AI's aggregate utilization effect comes from personalized preventive care networks, which reduced emergency room visits from 17.3 percent to 14.6 percent of members and urgent care utilization from 10.1 percent to 4.5

32 Kathryn Holston, Thomas Laubach, and John C. Williams, "Measuring the Natural Rate of Interest: International Trends and Determinants," Journal of International Economics 108 (2017): S59–S75.

33 Kurt G. Lunsford, "Productivity Growth and Real Interest Rates in the Long Run," Economic Commentary 2017-20 (Federal Reserve Bank of Cleveland, November 15, 2017), https://www.clevelandfed.org/publications/economic-commentary/2017/ec-201720-productivity-real-interest-rates-long-run.

34 Lawrence H. Summers and Lukasz Rachel, "On Falling Neutral Real Rates, Fiscal Policy and the Risk of Secular Stagnation," Brookings Papers on Economic Activity, BPEA Conference Drafts, March 2019, 1–54.

35 Benjamin H. Harris, Neil Mehrotra, and Eric So, The Fiscal Frontier: Projecting AI's Long-Term Impact on U.S. Old-Age Entitlement Spending (Brookings Institution, 2025).

36 Mohammad R. Arbabshirani et al., "Advanced Machine Learning in Action: Identification of Intracranial Hemorrhage on Computed Tomography Scans of the Head with Clinical Workflow Integration," npj Digital Medicine 1, no. 1 (2018): 1–7. https://doi.org/10.1038/s41746-017-0015-z.

37 Somya D. Mohanty et al., "Machine Learning for Predicting Readmission Risk among the Frail: Explainable AI for Healthcare," Patterns 3, no. 1 (2021): 100395. https://doi.org/10.1016/j.patter.2021.100395.

percent over three years.[38] Countervailing these reductions, however, is the risk of overdiagnosis, the identification of asymptomatic conditions that would not have caused harm, which can generate unnecessary treatment, physical and financial harm to patients, and upward pressure on aggregate utilization.[39]

AI's potential to reduce the price of health care services is meaningful but historically complicated. Program-specific evidence can be encouraging; for example, an automated diabetic retinopathy screening system reduced costs by 23.3 percent relative to standard care,[40] and in a simulation model, AI-assisted colonoscopy screening prevented over 2,000 deaths and saved an estimated $290 million annually.[41] The largest near-term cost reduction channel, however, may be administrative. Roughly one quarter of the approximately $3.8 trillion the United States spent on health care in 2019 went toward administrative functions,[42] and one analysis projected that reduced administrative costs would account for more than one third of the $360 billion (in 2019 dollars) AI is expected to cut from health care spending over a five-year horizon.[43] Against this evidence, a broader literature cautions that technological advancement has historically been a driver of rising health expenditures, with one review attributing an average of 35 percent of health expenditure growth to technological change, as breakthroughs expand the treatment frontier, render prior therapies obsolete, and increase utilization through more accessible diagnosis.[44]

The mortality channel is perhaps the most consequential for long-run entitlement spending because reductions in age-specific death rates unambiguously expand the population eligible for Social Security and Medicare benefits. This generates fiscal pressure that may offset or exceed savings from cost and utilization improvements. The historical record demonstrates that rapid mortality decline is achievable: in Japan between 1948 and 1958, the unweighted average annual decline in age-specific death rates was approximately 6 percent.[45] Moreover, some studies project sharp declines in mortality associated with greater investment in AI in general and longevity-enhancing research in particular. For example, one study projects that annual mortality improvements for individuals aged 50 and over will range from 2.2 to 3.6 percent between 2025 and 2040 with longevity-specific investment of $15 billion per year.[46] Both the historical and projected mortality declines are several times larger than the 0.73 percent annual reduction assumed in the Social Security Trustees' intermediate scenario,[47] although the projected declines are in-line with our modeling assumptions. Whether AI can produce mortality improvements of comparable magnitude in the United States remains uncertain, but population aging has already proven fiscally significant: population aging was associated with an 11.6 percent increase in health care spending between 1996 and 2013,[48] and projections suggest

38 Shirley Musich et al., "The Impact of Personalized Preventive Care on Health Care Quality, Utilization, and Expenditures," Population Health Management 19, no. 6 (2016): 389–97. https://doi.org/10.1089/pop.2015.0171.

39 Barbara K. Dunn et al., "Cancer Overdiagnosis: A Challenge in the Era of Screening," Journal of the National Cancer Center 2, no. 4 (December 1, 2022): 235–42. https://doi.org/10.1016/j.jncc.2022.08.005.

40 Spencer D. Fuller et al., "Five-Year Cost-Effectiveness Modeling of Primary Care-Based, Nonmydriatic Automated Retinal Image Analysis Screening Among Low-Income Patients With Diabetes," Journal of Diabetes Science and Technology 16, no. 2 (March 1, 2022): 415–27. https://doi.org/10.1177/1932296820967011.

41 Miguel Areia et al., "Cost-Effectiveness of Artificial Intelligence for Screening Colonoscopy: A Modelling Study," The Lancet Digital Health 4, no. 6 (June 1, 2022): e436–44. https://doi.org/10.1016/S2589-7500(22)00042-5.

42 Nikhil R. Sahni, Brandon Carrus, and David M. Cutler, "Administrative Simplification and the Potential for Saving a Quarter-Trillion Dollars in Health Care," JAMA 326, no. 17 (November 2, 2021): 1677–78. https://doi.org/10.1001/jama.2021.17315.

43 Sahni, Carrus, and Cutler, "Administrative Simplification," 1677–78.

44 Alberto Marino and Luca Lorenzoni, "The Impact of Technological Advancements on Health Spending: A Literature Review" (Paris: OECD, August 22, 2019). https://doi.org/10.1787/fa3bab05-en.

45 Harris, Mehrotra, and So, Fiscal Frontier, 13.

46 Dror, David M. "Breaking the Mortality Curve: Investment-Driven Acceleration in Life Expectancy and Insurance Innovation." Risks, 13(7): 122 (June 2025). https://doi.org/10.3390/risks13070122.

47 Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds, 2025 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds (Social Security Administration, 2025). https://www.ssa.gov/oact/TR/2025/index.html.

48 Joseph L. Dieleman et al., "Factors Associated With Increases in US Health Care Spending, 1996–2013," JAMA 318, no. 17 (November 7, 2017): 1668–78. https://doi.org/10.1001/jama.2017.15927.

the age-sex mix of the population will continue to contribute meaningfully to spending growth through the middle of the current decade,[49] even if less than the effects of rising medical prices and utilization. Thus, the net fiscal impact of a health productivity shock depends meaningfully on the relative magnitude of the mortality, utilization, and price channels.

Another means through which to explore the historical variability of key macroeconomic indicators is to view their variability over previous decades within the United States. This analysis is undertaken in Appendix Table 1, where cumulative change by decade is examined for labor productivity (not directly modeled, but informs changes to economic growth), nominal GDP, marginal labor share, labor force participation rate, and age-specific mortality. The table is supplemented with the cumulative change of the specific parameters utilized in each scenario in the AI-population model described below over a ten-year period and includes percentile rankings of where these parameters fall within the historical distribution of the past six decades. Of note, most parameters considered in this analysis tend to fall between the 17th and 50th percentile of their respective distributions; the exceptions are age-specific mortality rates, which are in the 67th percentile for the baseline, scenario 1, and scenario 2 and below the minimum of the historical distribution for scenarios 3 and 4, and marginal labor share and labor force participation rate in scenarios 2 and 4, which fall below the minimum of their respective historical distributions. Rationales for parameter selection are described in the appendix below.

49 Sean P. Keehan et al., "National Health Expenditure Projections, 2016–25: Price Increases, Aging Push Sector To 20 Percent Of Economy," Health Affairs 36, no. 3 (March 2017): 553–63. https://doi.org/10.1377/hlthaff.2016.1627.

C. Contemporary Estimates of the AI Shock

Recent economic research offers a range of estimates for the magnitude, timing, and persistence of productivity gains from AI, reflecting both uncertainty about the technology's capabilities and disagreement over its diffusion and general-equilibrium effects. Task-based macroeconomic frameworks that aggregate micro-level performance improvements across exposed activities tend to yield moderate but economically meaningful productivity gains. Using such a framework, Acemoglu (2025) estimates that current and near-term AI applications are likely to raise aggregate TFP (total factor productivity) by no more than 0.66 percent cumulatively over a decade under an optimistic reading of task-level evidence, with the central estimate falling below 0.53 percent once the greater difficulty of automating complex, context-dependent tasks is taken into account, implying only a modest acceleration in annual growth rates relative to recent experience.[50] By contrast, Aghion and Bunel (2024), drawing on historical analogies to prior general-purpose technologies, project an increase in annual productivity growth of 0.8 to 1.3 percentage points over the next ten years; applying the same task-based framework as Acemoglu but with a more expansive reading of task-level evidence, they obtain a median estimate of approximately 0.7 percentage points annually over ten years.[51]

Institution-based forecasting exercises generally fall between these bounds. The OECD's micro to macro simulations project that AI could raise annual aggregate TFP growth by 0.25 to 0.6 percentage points over a ten year horizon in the United States under main scenarios, with estimates for other advanced economies of similar but somewhat lower magnitude, and larger effects in countries and sectors characterized by greater

50 Daron Acemoglu, "The Simple Macroeconomics of AI," Economic Policy 40, no. 121 (2025): 13–58.

51 Philippe Aghion and Simon Bunel, "AI and Growth: Where Do We Stand?" Policy Note, EmergingTech Economic Research Network, Federal Reserve Bank of San Francisco, 2024. https://www.frbsf.org/wp-content/uploads/AI-and-Growth-Aghion-Bunel.pdf.

exposure to AI-intensive services.[52] Similarly, the Penn Wharton Budget Model estimates that generative AI could raise the level of GDP by approximately 1.5 percent by 2035, with annual productivity growth temporarily boosted—peaking at about 0.2 percentage points per year in 2032—before largely reverting to trend as adoption saturates.[53] Across these approaches, AI is generally modeled as producing a persistent level effect on output rather than a permanent increase in the long run growth rate.

A related literature emphasizes uncertainty surrounding both diffusion and tail outcomes. Expert elicitation exercises reveal substantial dispersion in projected growth paths across respondent groups: under baseline conditions, median forecasts cluster around 2.5 percent annual GDP growth, modestly above trend, while a rapid AI scenario, conditional on AI systems surpassing human performance across many cognitive tasks, yields median forecasts of approximately 4 percent annualized GDP growth.[54] At the same time, several reviews caution that measured aggregate productivity gains may lag underlying technological progress because of adjustment costs, organizational frictions, and complementary intangible investments, giving rise to a productivity "J curve" similar to that observed in earlier technological transitions.[55]

In summary, the literature shows that even optimistic AI scenarios are unlikely to replicate the sustained, multi-decade productivity accelerations of the mid-twentieth century, although these projections are subject to high degrees of uncertainty. However, prior studies suggest that AI could plausibly generate transitional productivity shocks of sufficient magnitude and duration to materially affect fiscal outcomes over standard budget windows.

52 Francesco Filippucci, Peter Gal, and Matthias Schief, Miracle or Myth? Assessing the Macroeconomic Productivity Gains from Artificial Intelligence, OECD Artificial Intelligence Papers, No. 29 (OECD Publishing, 2024). https://doi.org/10.1787/b524a072-en.

53 Alexander Arnon, "The Projected Impact of Generative AI on Future Productivity Growth," Penn Wharton Budget Model, September 8, 2025. https://budgetmodel.wharton.upenn.edu/p/2025-09-08-the-projected-impact-of-generative-ai-on-future-productivity-growth/.

54 Ezra Karger et al., "Forecasting the Economic Effects of AI," NBER Working Paper No. 35046, 2026. https://doi.org/10.3386/w35046.

55 Erik Brynjolfsson, Daniel Rock, and Chad Syverson, "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies," American Economic Journal: Macroeconomics 13, no. 1 (2021): 333–372.

Methodology

To simulate the fiscal impact of AI-driven shocks, we construct a multi-module simulation model that tracks the effects of changes through the federal budget over a twelve-year horizon from 2025 to 2036. The model is organized around parameters (described and justified in the Appendix) that are shiftable given scenario assumptions, allowing for comparison between the baseline and an alternative budget for each scenario. The baseline budget replicates projected federal spending and revenues under current law, using CBO projections as reference. The alternative budgets introduce AI-driven shocks and trace the downstream consequences for federal program enrollment, spending, revenues, and net interest costs.

A. Population Projections

The population module is the foundation of the model and a channel through which AI shocks propagate to the federal budget. We construct separate baseline and alternative population projections by single year of age and sex for each year of the projection window. In both population modules, starting population counts for the year 2024 by age and sex are sourced from the Census Bureau's most recent national population estimates.[56] In each projection year, the surviving population in each age-sex cohort is calculated by applying the prior year's age-sex mortality rate to the prior year age-sex cohort; we also add a birth

56 U.S. Census Bureau, "Annual Estimates of the Resident Population by Single Year of Age and Sex for the United States: April 1, 2020 to July 1, 2024 (NC-EST2024-SYASEXN)," National Population by Characteristics: 2020–2024, accessed March 16, 2026, https://www.census.gov/data/tables/time-series/demo/popest/2020s-national-detail.html.

cohort split by sex ratio at age 0 of the current projection year. Age-sex specific mortality rates are drawn from the Social Security Administration's (SSA) Period Life Table for 2022, as used in the 2025 Trustees Report.[57] Age-specific fertility rates are applied to five-year female cohorts and are drawn from provisional 2024 natality data published by the National Center for Health Statistics (NCHS),[58] with the sex ratio at birth set consistent with historical trends from NCHS vital statistics.[59]

The baseline population mortality reduction rate of 0.73 percent per year—consistent with the SSA Trustees Report's intermediate assumptions—can be altered in the alternative population module with a scenario-specified reduction rate. This parameterization is intended to capture AI-driven advances in diagnostics, drug discovery, and personalized medicine that may meaningfully compress mortality rates beyond their historical trend.

The baseline population module labor force (18-64) is constructed using labor force participation rates (LFPRs) which are applied separately by sex and age band, utilizing participation rate schedules from SSA Actuarial Study No. 127.[60] In the alternative population module, LFPRs can be modified through a constant shift, phased in incrementally at 25 percent of the shift per year over the first four years, producing an alternative labor force estimate for each projection year.

57 Social Security Administration, Office of the Chief Actuary, "Period Life Table, 2022, as Used in the 2025 Trustees Report," accessed March 16, 2026, https://www.ssa.gov/oact/STATS/table4c6.html.

58 Joyce A. Martin, Brady E. Hamilton, and Michelle J.K. Osterman, "Births: Provisional Data for 2024," Vital Statistics Rapid Release, Report No. 38 (National Center for Health Statistics, April 2025), Table 1, "Births and Birth Rate, by Age of Mother: United States, Final 2023 and Provisional 2024," https://www.cdc.gov/nchs/data/vsrr/vsrr038.pdf.

59 T.J. Mathews and Brady E. Hamilton, "Trend Analysis of the Sex Ratio at Birth in the United States," National Vital Statistics Reports 53, no. 20 (National Center for Health Statistics, June 14, 2005), https://www.cdc.gov/nchs/data/nvsr/nvsr53/nvsr53_20.pdf.

60 Polina Vlasenko and Judith Aboagye, "Employment Projections in the 2022 Social Security Trustees Report," Actuarial Study No. 127 (Social Security Administration, Office of the Chief Actuary, March 2023), Tables 4–5, "Civilian Labor Force Participation Rates, Men and Women, by Age Group," https://www.ssa.gov/OACT/NOTES/pdf_studies/study127.pdf.

These parameters are designed to reflect changes in labor force participation among working-age adults associated with AI-driven shocks.

B. Federal Spending

Federal spending projections are organized into five modules: Medicare, Medicaid, Social Security, income support programs, and discretionary spending. The first four are directly linked to the baseline and alternative population modules; discretionary spending follows an independent growth path tied to CBO's 2026 projections.[61] Each spending module produces both a baseline and alternative spending projection. The sum of baseline mandatory spending is used to calculate residual mandatory spending from our model relative to CBO projections of total mandatory spending. The sum of alternative mandatory spending, alternative discretionary spending, and the mandatory spending residual constitutes total spending under an AI-shock.

Medicare. Medicare spending is projected separately for Parts A, B, and D. In each case, total expenditure per year is calculated as the product of the enrolled population and average per-beneficiary spending. The enrolled population is defined as the total population aged 65 and older drawn from the respective population module. Baseline average per-beneficiary spending for each part is sourced from Table V.D1 of the 2025 Medicare Trustees Report,[62] with values for 2035 and 2036 extrapolated using the implied nine-year geometric growth rate. Baseline inflation rates for Parts A, B, and D are taken from Table II.D1 of the same report,[63] and are utilized to derive implied utilization growth rates.

61 Congressional Budget Office, The Budget and Economic Outlook: 2026 to 2036, February 2026, Table 3-1, "CBO's Baseline Projections of Outlays," 60, https://www.cbo.gov/publication/61882.

62 Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds, 2025 Annual Report of the Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds (Centers for Medicare & Medicaid Services, June 18, 2025), Table V.D1, "HI and SMI Average Incurred per Beneficiary Costs," 201. https://www.cms.gov/oact/tr/2025.

63 Ibid., Table II.D1, "Components of Increase in Medicare Incurred Expenditures by Part," 21.

In the alternative scenarios, the enrolled population and per-beneficiary cost can adapt in response to an AI shock, with the enrolled population derived from the alternative population module's 65+ age group. Per-beneficiary spending is adjusted through utilization and price parameters. The utilization parameter allows for scenarios in which AI-driven changes in preventive care and diagnostic accuracy increase or decrease per-beneficiary utilization relative to the baseline. The price adjustment parameter allows for changes to the inflation rate driven by AI shocks to Medicare input costs.

Medicaid. Medicaid spending is projected as enrollment multiplied by per-enrollee spending, summed over eligibility groups. Medicaid enrollment is projected by eligibility group (Child, New Adult Group, Other Adult Group, Disabled, Aged), applying group-specific enrollment rates to the corresponding population cohorts from respective population modules. Enrollment rates are derived from MACPAC's (Medicaid and CHIP [Children's Health Insurance Program] Payment and Access Commission's) FY 2023 full-year equivalent enrollment data.[64] Baseline per-enrollee spending by eligibility group is sourced from MACPAC's FY 2023 benefit spending data.[65]

Like the Medicare module, alternative scenarios allow for enrollment shifts in response to the alternative population module, while per-enrollee spending adjusts through utilization and inflation parameters. Baseline utilization rates are derived from average Medicaid expenditure growth rates[66] and inflation expectations.[67] An additional parameter is included that allows for a constant fraction of workers displaced from the labor force relative to the baseline to be added to the Other Adult Group.

Social Security. Social Security projections cover both OASI and DI. Total expenditures are calculated as total enrollees times mean expenditures under both programs for the baseline and alternative spending projections. Baseline OASI total expenditures are drawn from CBO's February 2026 projections.[68] Baseline mean per-beneficiary OASI benefits are calculated by dividing total expenditures by the projected number of retirement-age beneficiaries from respective population modules, with a parameter indicating the fixed share of the 65-and-older population assumed to be receiving Social Security benefits. In alternative scenarios, the OASI beneficiary count expands in line with the alternative population module for the 65-and-older cohort, and total OASI expenditure adjusts accordingly at the baseline mean per-beneficiary benefit level.

DI projections follow a parallel structure, with the baseline utilizing actual DI beneficiary counts in place of population module projections. Baseline DI enrollees and expenditures are drawn from CBO's February 2026 Social Security Disability Insurance baseline.[69] Baseline mean DI expenditures are total expenditures divided by enrollees. In the alternative scenarios, an additional parameter

64 Medicaid and CHIP Payment and Access Commission (MACPAC), "Exhibit 15: Medicaid Full-Year Equivalent Enrollment by State and Eligibility Group, FY 2023," MACStats: Medicaid and CHIP Data Book, February 2026, accessed March 18, 2026, https://www.macpac.gov/wp-content/uploads/2026/01/EXHIBIT-15.-Medicaid-Full-Year-Equivalent-Enrollment-by-State-and-Eligibility-Group-FY-2023.pdf

65 Medicaid and CHIP Payment and Access Commission (MACPAC), MACStats: Medicaid and CHIP Data Book, February 2026, Exhibit 22, "Medicaid Benefit Spending Per Full-Year Equivalent (FYE) Enrollee by State and Eligibility Group, FY 2023," 57. https://www.macpac.gov/macstats/.

66 Centers for Medicare & Medicaid Services, Office of the Actuary, "National Health Expenditure Projections 2024–2033," Table 17, "Health Insurance Enrollment and Enrollment Growth Rates," accessed March 17, 2026, https://www.cms.gov/data-research/statistics-trends-and-reports/national-health-expenditure-data/projected.

67 Federal Reserve Bank of Cleveland, "Inflation Expectations," 10-Year Expected Chart, June 1, 2024, accessed March 17, 2026, https://www.clevelandfed.org/indicators-and-data/inflation-expectations.

68 Congressional Budget Office, The Budget and Economic Outlook: 2026 to 2036, February 2026, Table 3-2, "CBO's Baseline Projections of Mandatory Outlays, Adjusted to Exclude the Effects of Timing Shifts," 64. https://www.cbo.gov/publication/61882.

69 Congressional Budget Office, "Baseline Projections: Social Security Disability Insurance," February 2026, https://www.cbo.gov/data/baseline-projections-selected-programs.

is included that allows for a constant fraction of workers displaced from the labor force relative to the baseline to be added to the DI beneficiary count.

Income Support Programs. Five income support programs are modeled: Premium Tax Credits and related spending (PTC), the CHIP, Food and nutrition assistance (FOOD), Supplemental Security Income (SSI), and Unemployment Compensation (UC). Baseline expenditures for each program are drawn from CBO's February 2026 mandatory outlay projections.[70]

The alternative scenarios for income support programs employ an elasticity-based scaling approach, which differs from the population-count methodology used for Medicare, Medicaid, and Social Security. For each program other than UC, alternative expenditure in year t is calculated as:

$$Spending\ alt_t = Spending\ base_t \times (1 + \varepsilon \times \theta \times \Delta NILF\%_{t-1})$$

where ε is the program-specific elasticity of spending with respect to the percent change in the NILF (Not in Labor Force) population aged 18–64 in the previous year, and $\Delta NILF\%_{t-1}$ is the percent change in the NILF population between the baseline and alternative scenarios in year t-1. A supplemental parameter, θ, applies the elasticity-based adjustment to a fixed share, 30 percent across the baseline and alternative scenarios, of the projected change in the NILF population.[71] The alternative spending formula is applied independently in each projection year without compounding.

Elasticities are estimated from regression analysis using historical NILF data from IPUMS ACS (American Community Survey) microdata[72] and Office of Management and Budget (OMB) historical spending data[73] from 2000-2024, excluding any year with a recession and the following year if the recession lasted longer than one quarter. Elasticities for PTC, CHIP, FOOD, and SSI were estimated as the log difference in annual program spending on the one-year-lagged log difference in the NILF population and a contemporaneous log-differenced program-specific price index, with no constant. [74]

Residual Mandatory Spending. Residual mandatory spending is calculated as the difference between CBO's mandatory outlay projections and the sum of the baseline outlay projections for the explicitly-modeled mandatory programs above. Residual mandatory spending reflects both modeled and non-modeled differences between the model's baseline mandatory outlay projections and CBO's baseline.

70 Congressional Budget Office, The Budget and Economic Outlook: 2026 to 2036, February 2026, Table 3-2, "CBO's Baseline Projections of Mandatory Outlays, Adjusted to Exclude the Effects of Timing Shifts," 64–65, https://www.cbo.gov/publication/61882.

71 We are unaware of evidence showing precise take-up rates for new labor force drop outs for these various income-support programs. Given that the recipiency rate for unemployment insurance benefits tends to hover around 25-30 percent (Serdar Birinci & Kurt See, 2023. "Labor Market Responses to Unemployment Insurance: The Role of Heterogeneity," American Economic Journal: Macroeconomics, American Economic Association, vol. 15(3), pages 388-430, July.), and that tabulations from the Survey of Income and Program Participation reveal that around 35 percent of labor force dropouts ages 18-64 who involuntarily leave the labor force receive services from at least one income support program (United States Census Bureau. "2024 SIPP Data." Survey of Income and Program Participation, reference period January–December 2023. Released 2024. https://www.census.gov/programs-surveys/sipp/data/datasets/2024-data/2024.html.), we selected 30 percent as the share of new labor force drop outs who receive income support services.

72 Steven Ruggles et al., IPUMS USA: Version 16.0 [dataset] (IPUMS, 2025). https://doi.org/10.18128/D010.V16.0.

73 United States Office of Management and Budget, Historical Tables: Budget of the U.S. Government, Fiscal Year 2026, Table 8.5, "Outlays for Mandatory and Related Programs: 1962–2030" (Office of Management and Budget, 2025). https://www.whitehouse.gov/omb/budget/historical-tables/.

74 FOOD spending is controlled for CPI Food at Home (CUSR0000SAF11); PTC and CHIP spending are controlled for CPI Medical Care (CPIMEDSL); SSI and UC spending are controlled for CPI-U (CPIAUCSL). The UC elasticity follows the same specification, except that the percentage change in the NILF population enters contemporaneously rather than with a lag. All price index series are published by the U.S. Bureau of Labor Statistics and retrieved from the Federal Reserve Bank of St. Louis FRED database (https://fred.stlouisfed.org/).

Discretionary Spending. Defense and non-defense discretionary spending baselines are drawn from CBO's February 2026 outlay projections.[75] In the alternative scenarios, each category is allowed to grow at an alternative annual rate, with certain scenarios modeling a military arms race and associated escalation in defense spending.

C. GDP, Revenues, and Interest Costs

GDP. The baseline nominal GDP path is drawn directly from CBO's February 2026 economic projections.[76] In alternative scenarios a parameter governing GDP growth is allowed to reflect the macroeconomic consequences of an AI shock. The change in GDP relative to the baseline is decomposed into labor, capital (non-corporate), and corporate income shares, utilizing parameters for the specified shares of new growth attributable to each source.[77] This decomposition is necessary to apportion the GDP shock across the revenue module described below.

Revenues. Individual income tax revenues are projected separately for individual labor and capital income, with a parameter controlling the fixed share of net business income assumed to be attributable to either capital or labor (0.666 to labor across the baseline and alternative scenarios). For individual labor income, the taxable base and baseline revenue projections are sourced and derived from CBO's February 2026 revenue projections by category.[78] Baseline individual labor income tax revenue is calculated as the individual labor tax base times the implied tax rate on individual labor income. CBO's calculated effective marginal tax rate on individual labor income[79] is applied to the additional individual labor income from economic growth, producing the alternative individual labor income tax revenue. To reflect revenue derived from the Medicare payroll tax, we add 2.9 percentage points to the effective marginal tax rate on additional individual labor income. (We do not model additional changes to OASDI (Old-Age, Survivors, and Disability Insurance) payroll tax revenues as we assume that these are fiscally neutral over the long run.) A parallel structure is used for individual (non-corporate) capital income, with the individual capital income taxable base and revenue projections similarly sourced and derived from the same CBO release,[80, 81] producing baseline and alternative individual capital income.

Corporate tax revenues follow a similar model and are projected using CBO's projections of income subject to corporate taxation[82] and baseline corporate revenue.[83] The implied corporate tax rate is held constant in the alternative scenarios, with revenues adjusting in proportion to changes in the corporate income base driven by the GDP decomposition. Payroll taxes follow the CBO baseline[84] and are not adjusted in the alternative scenario, as the model does not separately project payroll tax base effects of labor force changes.

Residual Revenues. Similar to mandatory spending, a residual revenue adjustment is calculated as the difference between CBO's total baseline revenue projections and the sum of the explicitly modeled

75 Congressional Budget Office, The Budget and Economic Outlook: 2026 to 2036, February 2026, Table 3-1, "CBO's Baseline Projections of Outlays," 60, https://www.cbo.gov/publication/61882.
76 Congressional Budget Office, The Budget and Economic Outlook: 2026 to 2036, February 2026, Table D-1, "CBO's Economic Projections, by Calendar Year," 155, https://www.cbo.gov/publication/61882.
77 Congressional Budget Office, "Economic Projections," tab "3. Fiscal Year," February 2026, accessed March 17, 2026, https://www.cbo.gov/data/budget-economic-data#4.
78 Congressional Budget Office, "Revenue Projections by Category," tab "3. Individual Income Tax Details," February 2026, accessed March 17, 2026, https://www.cbo.gov/data/budget-economic-data#7.
79 Congressional Budget Office, "Tax Parameters and Effective Marginal Tax Rates," tab "2. EMTR on Labor," February 2026, accessed March 17, 2026, https://www.cbo.gov/data/budget-economic-data#10.
80 Congressional Budget Office, "Revenue Projections by Category," tab "3. Individual Income Tax Details," February 2026, accessed March 17, 2026, https://www.cbo.gov/data/budget-economic-data#7.
81 Congressional Budget Office, "Tax Parameters and Effective Marginal Tax Rates," tab "3. EMTR on Capital," February 2026, accessed March 17, 2026, https://www.cbo.gov/data/budget-economic-data#10.
82 Congressional Budget Office, "Revenue Projections by Category," tab "8. Corporate Profits," February 2026, accessed March 17, 2026, https://www.cbo.gov/data/budget-economic-data#7.
83 Congressional Budget Office, "Revenue Projections by Category," tab "1. Revenue Projections," February 2026, accessed March 17, 2026, https://www.cbo.gov/data/budget-economic-data#7.
84 Ibid.

baseline revenue components. The residual revenue adjustment reflects both modeled and non-modeled differences between the model's baseline revenue projections and CBO's baseline.

Interest Costs. Baseline net interest costs are sourced from CBO's February 2026 Budget and Economic Outlook.[85] Alternative net interest costs are computed in two components. First, the incremental interest cost arising from the AI-driven primary deficit shock is estimated using a vintage debt-service matrix. In each projection year, the primary deficit shock—defined as the difference between the alternative and baseline primary deficits—represents new borrowing that accumulates at prevailing Treasury rates sourced from CBO. The matrix is lower-triangular: each vintage of new borrowing incurs interest in the year it is issued and all subsequent projection years, with a half-year rate convention applied in the issuance year to reflect mid-year borrowing. Total incremental debt service in each calendar year is the sum of interest costs across all outstanding vintages.

Second, 30 percent[86] of the model's debt held by the public is assumed to roll over each calendar year; interest on this portion is computed at the CBO implicit interest rate multiplied by a scalar parameter. Beginning-of-year debt levels are anchored to CBO projections[87] and adjusted by the cumulative primary deficit shock and cumulative difference between alternative and baseline interest costs. The implicit interest rate is derived as CBO baseline interest cost divided by the CBO debt level in each respective year. Alternative net interest costs in any year are thus the sum of incremental debt service from the vintage matrix, 70 percent of the model debt stock multiplied by the CBO implicit interest rate, and the scaled interest cost on the 30 percent rolled-over portion of the model debt stock. A scalar parameter allows for interest rate adjustments on the rolled-over debt portion and on all vintages in the debt-service matrix, calibrated to reflect changes in r* associated with the alternative scenario's nominal GDP growth rate.

85 Congressional Budget Office, The Budget and Economic Outlook: 2026 to 2036, February 2026, Table 1-1, "CBO's Baseline Budget Projections," 13, https://www.cbo.gov/publication/61882.

86 Julian Kozlowski and Samuel Jordan-Wood, "Assessing the Costs of Rolling Over Government Debt," Economic Synopses, no. 13 (Federal Reserve Bank of St. Louis, June 2, 2023). https://www.stlouisfed.org/on-the-economy/2023/jun/assessing-the-costs-of-rolling-over-government-debt.

87 Congressional Budget Office, The Budget and Economic Outlook: 2026 to 2036, Table 1-3, 20.

D. Fiscal Aggregates

The fiscal aggregates module assembles the outputs of the preceding modules into a unified alternative fiscal picture for each projection year. On the spending side, each alternative scenario's expenditure components (Medicare, Social Security, Medicaid, income support programs, and discretionary spending) are summed with residual mandatory spending to produce total outlays. On the revenue side, each alternative scenario's revenues (labor income tax, non-corporate capital income tax, corporate tax, and payroll tax) and residual revenues are summed to produce total revenues. The difference between total outlays and total revenues produces the primary deficit for each scenario in each year.

The CBO baseline primary deficit and net interest costs are sourced directly from CBO's February 2026 Budget and Economic Outlook and serve as the fixed reference path against which each alternative scenario is compared. The AI-driven fiscal shock in each projection year is the difference between the alternative total deficit—computed from the scenario's alternative primary deficit plus alternative interest costs—and the CBO baseline total deficit. Lastly, rather than prescribe a phase-in path for each parameter in each scenario, we apply an assumed post-simulation parameter which allows total deficit shocks to be phased-in at a rate of 25 percent per year beginning in 2026, such that full AI-driven fiscal shocks are not realized until 2029 and onward. (The sole exception is with LFPR, which is immediately phased-in).

TABLE 1

Parameter Values by Scenario

		Scenario				
Module	**Parameter**	**0 Baseline**	**1 Traditional Productivity Shock**	**2 Labor Market Shock**	**3 Health Shock**	**4 Disruptive Shock**
Population	Mortality Reduction	0.0073	0.0073	0.0073	0.0300	0.0200
	LFPR Adjustment	0	0	-3	0	-3
Medicare (Parts A, B,D)	Utilization Adjustment	0.00	0.00	0.00	0.01	0.01
	Price Adjustment	0.000	-0.005	-0.005	-0.010	-0.005
Medicaid	Share of New Unemployed	0.35	0.30	0.35	0.30	0.35
	Utilization Adjustment	0.00	0.00	0.00	0.01	0.01
	Price Adjustment	0.000	-0.005	-0.005	-0.010	-0.005
Social Security	OASI Share of 65+	0.96	0.96	0.96	0.98	0.97
	DI Share of New Labor Force Dropouts	0.2	0.2	0.1	0.2	0.1
Income Support (Elasticities)	Premium Tax Credits and Related Spending	3.766	3.766	3.766	3.766	3.766
	Children's Health Insurance Program	-0.595	-0.595	-0.595	-0.595	-0.595
	Supplemental Nutrition Assistance Program	2.543	2.543	2.543	2.543	2.543
	Supplemental Security Income	0.714	0.714	0.714	0.714	0.714
	Unemployment Compensation	4.095	4.095	4.095	4.095	4.095
	Child Nutrition	2.543	2.543	2.543	2.543	2.543
Discretionary	Defense Spending Growth	0.019*	0.015	0.017	0.017	0.022
	Non-defense Spending Growth	0.014*	0.010	0.012	0.012	0.014
Macroeconomic	Nominal GDP Growth	0.0398*	0.0558	0.0488	0.0488	0.0558
	Share of New Growth to Non-corporate Capital	0.28	0.28	0.43	0.28	0.43
	Share of New Growth to Labor	0.54	0.54	0.30	0.54	0.30
	Share of New Growth to Corporate Capital	0.18	0.18	0.27	0.18	0.27
Interest Matrix	Interest Cost	1.00	1.35	1.18	1.18	1.35

Note: values marked with an * are average growth values across the budget window.

Results

We utilize this model of AI impacts on the federal budget to estimate the ten-year impact of four representative shocks. Below, we present results for an array of economic and fiscal outcomes, including population, labor force, labor force participation rate, Medicare spending (parts A, B, and D), Medicaid spending, Social Security spending, income support spending, defense and non-defense discretionary spending, interest outlays, revenues from capital and labor, and, lastly, annual deficits and the stock of public debt as a share of GDP. We describe the various scenarios qualitatively below, list specific parameter values in Table 1, and justify the selected parameters in the Appendix.

Scenario Descriptions

Scenario 1 corresponds to a traditional productivity shock, similar in magnitude to the adoption of computers in the 1980s and the expansion of the internet in the 1990s. Mortality is unchanged as the productivity shock is generalized and unfocused on health. LFPR does not change. The delivery of health care becomes marginally more efficient, with corresponding modest decreases in pricing. Health care utilization stays constant. Discretionary government programs see efficiency gains as AI complements government labor. Nominal GDP growth rises sharply by about 1.5 percentage points, but the allocation across tax bases does not change. Interest rates remain constant.

Scenario 2 corresponds to a shock that disproportionately impacts the labor market, shifting the composition of new economic growth and displacing a moderate share of workers. Here, as with scenario 1, mortality is unaffected. However, under this scenario LFPR falls sharply—by a similar magnitude observed during the COVID-19 pandemic—and a substantial share of those displaced workers enroll in income support and entitlement programs. Health programs experience identical changes as scenario 1. Discretionary spending (both defense and non-defense) becomes more efficient with reduced outlays for labor, as AI technology is labor replacing, but not as much as in scenario 1. Nominal GDP growth rises moderately, but labor gains a markedly smaller share of the growth. Interest rates do not change.

Scenario 3 corresponds to a health focused shock, similar to the ones modeled in the precursor to this study.[88] Here, productivity gains are concentrated in the health sector, with attendant reductions in mortality and increased health care efficiency and utilization. Age-specific mortality rates fall sharply. Increased health care productivity raises utilization rates, but pricing falls simultaneously. Discretionary spending follows the same path as the prior scenario. Interest rates do not change.

Scenario 4 corresponds to an amalgamation of these three scenarios, which we will refer to as a “disruption” scenario. Health productivity rises and mortality rates fall, but not as much as in Scenario 3. LFPR experiences the same sharp reduction as in Scenario 2. Health utilization rises and pricing falls. A substantial share of labor market dropouts migrate into public health and income support programs. Defense spending grows more rapidly as the U.S. enters an arms race with competitors, while non-defense discretionary spending is unchanged from the baseline as ongoing investments in AI infrastructure and training offset efficiency gains. As with Scenario 3, nominal GDP rises faster and the increased income is primarily attributed to capital and corporate tax bases. Unlike the other three scenarios, increased demand leads to a higher neutral rate of interest, which raises interest rates throughout the budget window.

88 Harris, Mehrotra, and So, Fiscal Frontier.

Results

Population (total and age 65+). Despite sharp changes in mortality rates across scenarios 3 and 4, the ten-year duration of the simulation means that total populations change very little (Figure 1). In the baseline case, the total population is 339.4 million in 2036—with the same level for scenarios 1 and 2. The total population in 2036 increases to 343.1 million in scenario 3 and 341.5 million in scenario 4. The retirement-age population shows somewhat greater proportional variation compared to the total population. In 2036, the baseline age 65+ population (and that in scenarios 1 and 2) is 74.1 million. This increases to 77.1 million in scenario 3 and 75.8 million in scenario 4 (Figure 2).

Labor force and labor force participation rate. The baseline LFPR stays mostly constant at around 77.2 percent to 77.7 percent in the baseline, with identical levels for scenarios 1 and 3. In scenarios 2 and 4, the LFPR is 3 percentage points lower and thus sits at roughly 74.4 percent to 74.7 percent throughout the budget window after the phase in is completed (Figure 4). Since the size of the labor force is a function of both the LFPR and the total population, there is variation across all four scenarios. In the baseline and scenario 1, the 2036 labor force is 155.5 million. In scenario 3, the combination of lower mortality and constant (relative to the baseline) LFPR boosts the labor force to 156.0 million by 2036. Conversely, the labor force gradually shrinks in scenarios 2 and 4, falling to 149.5 million and 149.8 million, respectively, over 10 years (Figure 3).

Entitlement and income support spending. Spending on Medicare (parts A, B, and D), Medicaid, and Social Security (OASDI and DI) vary throughout the budget window due to factors such as health prices and utilization, as well as population, labor force, and mortality. Medicare spending, regardless of which "part," follows a similar path across scenarios. Relative to the baseline, spending falls slightly—by about 5 percent—in scenarios 1 and 2 by 2036, but it rises by about 8 percent in scenario 4 and by slightly less in scenario 3 (Figures 5, 6, and 7.). OASI expenditures are simply a function of the population and remain constant across scenarios 1 and 2 relative to the baseline—but rise annually by about $100 billion in scenario 3 and roughly $58 billion in scenario 4 (Figure 8). Social Security DI outlays stay constant in scenario 1 and mostly constant in scenario 3, but they rise by about $15 billion in 2036 under scenarios 2 and 4 (Figure 9). Medicaid spending falls moderately in scenarios 1 and 2 and rises moderately under scenario 3, but it increases sharply—by around $130 billion annually—under scenario 4 due to a combination of reduced LFPR, higher utilization, and more retirement age individuals (Figure 10).

Discretionary spending. Discretionary spending is wholly determined by the assumed growth rate of defense and non-defense spending, respectively. Non-defense discretionary spending has only a limited impact on total spending, even under scenario 1 in which the growth rate falls sharply relative to the baseline. Here, it is only about $50 billion less by the end of the budget window compared to the baseline (Figure 13). Similarly, defense spending changes have only a limited impact on total deficits, as savings are modest in the first three scenarios. The cost of an assumed arms race in scenario 4 slightly exceeds $350 billion cumulatively over the budget window relative to the baseline (Figure 12).

Tax revenues. Tax revenues depend critically on the assumed growth in nominal GDP but also depend on the allocation of that growth across labor, (non-corporate) capital, and corporate tax bases. Labor revenues rise across all four scenarios, but with a much more pronounced increase—around $1 trillion annually—under scenario 1, with an impact less than 56 percent that size in the other scenarios (Figure 14). Tax revenues from the capital tax base rise even more sharply across the various scenarios by 2036, ranging from an increase of about $180 billion in scenario 3 to a massive increase of over $500 billion (over 40 percent) in scenario 4 (Figure 15). Similarly, corporate tax revenues rise moderately across the first three scenarios—by between

roughly $110 billion to $200 billion—but increase by over $300 billion (over 50 percent) in scenario 4 (Figure 16).

Interest costs. Changes in interest expenditures are a function of changes in annual deficits and interest rates. Here, interest costs fall across the first three scenarios, but fall most sharply in scenario 1 (by about $280 billion annually by 2036). In scenario 4, interest expenditures increase by about $60 billion in 2036 (Figure 17).

Annual deficits. Annual deficits fall sharply relative to the baseline in scenario 1, slowly at first and then culminating in a decline of over $2.2 trillion (in GDP terms, about 5.0 percentage points) by 2036 (Figures 18 and 19). However, in subsequent scenarios, more than half the decline is recaptured due to various offsetting factors. In scenario 2, the impact is roughly halved. In scenario 3, the 2036 deficit falls by just roughly $700 billion relative to baseline (2.0 percentage points of GDP). The decline is only slightly larger for scenario 4, in which deficits in 2036 fall just over $870 billion (roughly 2.6 percentage points of GDP). Annual deficits as a percentage of GDP broken down by interest costs and primary deficits for the baseline and each scenario can be viewed in Figures 20, 21, 22, 23, and 24.

Sensitivity Analysis. As a robustness check on the underlying model, we test for differences in the 2036 total deficit given exogenous changes in r*, mortality rate decline, labor force participation rate, nominal GDP growth rate, discretionary defense spending rate, and discretionary non-defense spending rate from their specified scenario values (Figures 25, 26, 27, and 28). Each parameter is shifted around its scenario value in three descending and three ascending steps, with each step size equal to 5 percent of the parameters average value across all alternative scenarios. For each scenario, each parameter has the expected direction of effect on the total deficit: increases in r*, mortality rate decline, discretionary defense spending rate, and discretionary non-defense spending rate increase the total deficit in 2036; increases in labor force participation rate and nominal GDP growth rate decrease the total deficit in 2036.

Across all six parameters in all scenarios, changes in the nominal GDP growth rate have the largest effect on the 2036 deficit. For example, in Scenario 1, nominal GDP growth perturbed to its lowest growth rate causes a 2036 total deficit of almost $2 trillion relative to the Scenario 1 observed deficit of roughly $0.9 trillion; perturbed to its highest growth rate, the 2036 total deficit falls to roughly -$0.26 trillion. Conversely, changes to the labor force participation rate have the smallest impact on 2036 total deficits, with only roughly $50 billion separating the lowest and highest perturbations in Scenario 1.

Conclusion

Claims that AI will help grow the economy out of an unsustainable fiscal trajectory are understandable given the massive amounts of investment undertaken and the unharnessed capacity of the technology to boost productivity. Indeed, AI has the potential to improve many aspects of the fiscal outlook, including lower health costs, reduced discretionary spending, and most importantly, a larger tax base. Under a "traditional shock" scenario where these factors dominate, the ten-year fiscal impact is overwhelmingly positive: primary deficits turn negative, the annual deficit falls by over $2 trillion, and deficit as a share of GDP declines by almost 5 percentage points. Here, the techno-optimists are validated.

Yet, the idiosyncratic nature of this particular shock should give optimists pause. We see five primary factors mitigating downward pressure on budget deficits. One, improved health outcomes lead to longer lifespans, which in turn drive up entitlement spending. Two, displacement in the labor market means more people will be eligible for entitlement and income support payments, boosting these programs' cost. Three, the impact on defense spending may be positive if AI technology induces an arms race across international superpowers. Four, a changing composition of national income may push the tax base away from highly taxed labor income to less-taxed non-corporate capital and corporate profits. And lastly, increased demands for investment may raise the neutral rate of interest, which pushes up equilibrium interest rates and boosts interest expenditures, all else equal.

These factors partially counteract the benefits of a traditional productivity shock. Under three alternative scenarios (a labor market shock, a health shock, and a "disruptive" shock), the decline in annual deficits is halved at best and falls by two-thirds at worst. Nevertheless, across all four scenarios we examined, a productivity shock tied to AI will materially improve the budget outlook.

Appendix: Parameter Selection

This Appendix provides detailed empirical justification for the parameter choices across all four scenarios. The specific parameter choices are listed in Table 1 in the results section above.

Scenario 1. Scenario one is a traditional productivity shock, comparable to the experience of the late 1990s. In this scenario, mortality rates decline at the same rate as in the baseline scenario. Utilization rates for Medicare Parts A, B, and D, as well as Medicaid, also are not modified. Growth in the price of healthcare services purchased by these programs slows slightly due to efficiency gains facilitated by AI technologies. This decrease in the growth rate of healthcare prices is equal to the change modeled in the second scenario of Harris et al.[89] In this scenario, a slightly lower percentage of the newly unemployed workers receive insurance through Medicaid compared to the baseline. We assume that excess unemployment will be most concentrated among early career workers, consistent with the findings of Brynjolfsson et al.[90] Since the vast majority of young adults aged 18-25 with employer-sponsored health insurance are covered as dependents,[91] we assume that many unemployed early career workers would be able to obtain insurance through their families. Social Security spending is unchanged because mortality rates, and by extension the population in the Social Security coverage area, are unmodified from the baseline. Discretionary defense spending and non-defense spending grow substantially slower than at the baseline, as AI tools make government more efficient by cutting down on administrative costs and streamlining complex programs. Studies show that AI increases productivity for customer service[92] and consulting workers.[93] These gains are likely to extend to public sector employees, who use AI tools at nearly the same rate as those in the private sector.[94] AI could be particularly useful for minimizing improper payments, which are estimated to make up a large percentage of Federal spending.[95] Increased investment in AI tools is associated with improved quality and efficiency of audits in the private sector.[96] On the revenue side, widespread adoption of AI tools causes GDP to grow extremely rapidly—by 1.6 percentage points more quickly than baseline each year over the next decade. This is at the high end of the range for change in GDP growth predicted by Acemoglu when assuming that investments in AI will echo those for earlier automation technologies.[97] Just over half of this growth will go to labor rather than capital, the same proportion as in our baseline scenario, which reflects the latest data from Q1 2026.

Scenario 2. Scenario two is a labor market shock. Here, many workers at all career stages leave the workforce in the face of AI-driven automation. This results in LFPR falling by 3 percentage points, which is approximately equal to the LFPR shock experienced during the COVID-19 pandemic—but

89 Harris, Mehrotra, and So, Fiscal Frontier.

90 Erik Brynjolfsson, Bharat Chandar, and Ruyu Chen, "Canaries in the Coal Mine?: Six Facts about the Recent Employment Effects of Artificial Intelligence" (2025). https://digitaleconomy.stanford.edu/publication/canaries-in-the-coal-mine-six-facts-about-the-recent-employment-effects-of-artificial-intelligence/.

91 Matthew Rae, Gary Claxton, and Anthony Damico, "Dependent Coverage for Young Adults in Employer-Sponsored Health Plans," KFF, October 21, 2024, https://www.kff.org/private-insurance/dependent-coverage-for-young-adults-in-employer-sponsored-health-plans

92 Erik Brynjolfsson, Danielle Li, and Lindsey Raymond, "Generative AI at Work," Quarterly Journal of Economics 140, no. 2 (2025): 889–942.

93 Fabrizio Dell'Acqua et al., "Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of Artificial Intelligence on Knowledge Worker Productivity and Quality," Organization Science 37, no. 2 (2026): 403–423.

94 Christos Makridis, "AI Adoption Rapidly Growing in Public Sector," Gallup, March 11, 2026, https://www.gallup.com/workplace/702983/adoption-rapidly-growing-public-sector.aspx.

95 U.S. Government Accountability Office, Improper Payments: Information on Agencies' Fiscal Year 2024 Estimates, GAO-25-107753 (Washington, DC: GAO, March 11, 2025), https://www.gao.gov/products/gao-25-107753.

96 Anastassia Fedyk, James Hodson, Natalya Khimich, and Tatiana Fedyk, "Is Artificial Intelligence Improving the Audit Process?" Review of Accounting Studies 27, no. 3 (2022): 938–985, https://doi.org/10.1007/s11142-022-09697-x.

97 Acemoglu, "Simple Macroeconomics of AI."

without the immediate rebound experienced in 2020. This characterization of AI's impact on LFPR is consistent with the rapid AI progress scenario predicted by experts surveyed in Karger et al. in which AI's influence on LFPR "rivals the dip seen during the Covid-19 pandemic… but would reflect a more permanent impact on the labor force."[98] As in the first scenario, the utilization rates of Medicare Parts A, B, and D and Medicaid are unchanged, and price growth slows to the same degree. Job loss due to AI is sufficiently widespread in this scenario that we assume that unemployment will be relatively equally distributed between younger and older workers. As a result, the share of newly unemployed workers on Medicaid will not change from the baseline, as new unemployment will not be skewed towards younger workers who may have other avenues by which to obtain health insurance. Furthermore, a much lower percentage of new labor force dropouts will receive Social Security Disability Insurance than is assumed in the baseline, since most new labor force nonparticipants will not be disabled. This contrasts with the baseline, where disability is a leading cause of prime-age labor force nonparticipation, particularly among men.[99] Discretionary spending growth again slows from baseline thanks to AI efficiency gains, but not to the same degree as in the first scenario as AI replaces, rather than complements, workers. A systematic literature review of experimental studies investigating the effectiveness of human-AI collaboration found that, while AI systems alone most often outperformed humans alone, humans augmented by AI outperformed AI in a slight majority of studies.[100] Here, annual GDP growth accelerates by only 0.9 percentage points over the next decade, consistent with the lower end of the GDP growth estimate in Acemoglu.[101] Compared to the baseline scenario and scenario one, this growth is substantially skewed towards capital (70 percent), since AI development has been found to significantly reduce the labor income share.[102]

Scenario 3. The third scenario sees AI revolutionize human health. Many of the parameters in the third scenario are equivalent to the more extreme scenarios in Harris et al.[103] For example, scenario three simulates annual age-specific mortality reductions of 3 percent, the same as in the second and third scenarios from the original paper. This mortality reduction is facilitated by more effective, efficient healthcare delivery, which also contributes to accelerated utilization growth for both Medicaid and Medicare Parts A, B, and D. Increased quality of healthcare services increases demand for those services.[104] Though elevated demand should lead to increased healthcare prices, this effect is offset by AI-driven efficiency gains, most immediately in administrative costs. Studies have concluded that AI adoption could eliminate almost half of healthcare administrative costs, comprising $168 billion each year.[105] Consequently, in scenario three, we assume that use of AI in healthcare will cause a larger deceleration in price growth than previous scenarios. As in scenario one, the share of newly unemployed workers on Medicaid is expected to be slightly lower than at baseline, as job losses are concentrated among younger workers who might receive health insurance through other channels. On the other end of the age spectrum, the percentage of people aged 65 years and over who are receiving Social Security is set to increase. We believe that the longevity gains associated with AI use in healthcare will be less prominent among those who do not qualify for Social Security, most of whom do not qualify

98 Karger et al., "Forecasting the Economic Effects of AI."
99 Ryan Nunn, Jana Parsons, and Jay Shambaugh, "Labor Force Nonparticipation: Trends, Causes, and Policy Solutions," The Hamilton Project Strategy Paper (Washington, DC: Brookings Institution, October 2019), https://www.brookings.edu/articles/labor-force-nonparticipation-trends-causes-and-policy-solutions/.
100 Michelle Vaccaro, Abdullah Almaatouq, and Thomas Malone, "When Combinations of Humans and AI Are Useful: A Systematic Review and Meta-Analysis," Nature Human Behaviour 8, no. 12 (2024): 2293–2303.
101 Acemoglu, "Simple Macroeconomics of AI,"
102 Lei Chen et al., "The Impact of Artificial Intelligence on Labor Income Share: From the Perspective of Technological Progress Bias," Economic Analysis and Policy (2026).
103 Harris, Mehrotra, and So, Fiscal Frontier.
104 Martin Feldstein, "Quality Change and the Demand for Hospital Care," Econometrica 45, no. 7 (1977): 1681–1702.
105 Ophelie Lavoie-Gagne et al., "Artificial Intelligence as a Tool to Mitigate Administrative Burden, Optimize Billing, Reduce Insurance- and Credentialing-Related Expenses, and Improve Quality Assurance within Health Care Systems," Arthroscopy: The Journal of Arthroscopic & Related Surgery 41, no. 8 (2025): 3270–3275.

because of insufficient earnings.[106] Since AI use rates are highest among higher income groups,[107] we assume that mortality reductions facilitated by AI will primarily benefit higher income individuals rather than those with little to no income, such as late-arriving immigrants and infrequent workers. This is consistent with other research that finds that gains in life expectancy in the early 21st century were greater among higher income groups.[108] Scenario three simulates the same moderate reductions in discretionary spending as does scenario two. It also simulates the same moderate acceleration in GDP growth, though without the change in labor-capital share.

Scenario 4. While the first three scenarios simulate shocks primarily concentrated on a single area (productivity, labor, and health), the fourth and final scenario simulates disruptions to several factors at once, though often to a reduced degree. Scenario four features an age-specific mortality rate reduction scenario of 2 percent. This reduction, while smaller than scenario three in the present paper, is comparable to the mortality reductions in the first two scenarios of Harris et al.[109] Scenario four's health shock also affects Medicare and Medicaid, causing utilization rate increases equal to those simulated in scenario three, coupled with much less extreme price reductions. As in the second scenario of the current paper, scenario four features a labor shock that reduces LFPR by 3 percent. This job loss is widespread enough that the share of newly unemployed workers on Medicaid does not change from baseline. Again similar to scenario three, age-adjusted mortality reductions and longevity gains lead to the percentage of those 65 years old and older receiving Social Security to increase slightly. Unlike the previous scenarios, scenario four accelerates defense spending growth, as the United States invests in an AI arms race with its geopolitical rivals. One study argues that, unlike previous technological competitions—such as the nuclear arms race—in which the United States could maintain a lead thanks to a stockpile of difficult to replicate discoveries and difficult to obtain physical components, AI innovations diffuse extremely rapidly.[110] This means that the determinative factor will be the speed at which these innovations can be implemented, requiring continuous investment in "compute infrastructure that extends to the operational edge, technical talent that the military can develop and retain, and organizational machinery that compresses the cycle from commercial breakthrough to fielded capability." Furthermore, due to the disruptiveness of AI in scenario four, we also assume that non-defense discretionary spending growth does not slow, as any improvements in operational efficiency are canceled out by large public investments in AI development and infrastructure. The difficulty and expense of AI implementation could be exacerbated by supply chain vulnerabilities.[111] Finally, scenario four features the accelerated GDP growth of scenario one along with the capital-skewed growth of scenario three. This capital-skewed growth might increase the demand for capital, driving up real interest rates and consequently raising the cost of servicing the national debt.[112]

106 Social Security Administration, "Population Profile: Never Beneficiaries, Aged 60 or Older," Office of Retirement and Disability Policy (Washington, DC: SSA, May 2024), https://www.ssa.gov/policy/docs/population-profiles/never-beneficiaries.html.

107 Malihe Alikhani, Ben Harris, and Sanjay Patnaik, "How Are Americans Using AI? Evidence from a Nationwide Survey," Brookings Institution, November 25, 2025, https://www.brookings.edu/articles/how-are-americans-using-ai-evidence-from-a-nationwide-survey/.

108 Raj Chetty et al., "The Association between Income and Life Expectancy in the United States, 2001–2014," JAMA 315, no. 16 (2016): 1750–1766.

109 Harris, Mehrotra, and So, Fiscal Frontier.

110 Kyle Dotterrer, "You Can't Stockpile AI: Military Advantage in the Age of Algorithmic Diffusion," Modern War Institute, March 17, 2026, https://mwi.westpoint.edu/you-cant-stockpile-ai-military-advantage-in-the-age-of-algorithmic-diffusion/.

111 Hunter L. Clark, Jeffrey B. Dawson, and Shad Turney, "Will Mounting Supply Chain Strains Hamstring the AI Investment Boom?" Liberty Street Economics (Federal Reserve Bank of New York), May 11, 2026, https://doi.org/10.59576/lse.20260511.

112 James Pethokoukis, "What Would Be the Impact of an AI Boom on Interest Rates and Inflation?" Faster, Please! (AEI), July 13, 2023, https://www.aei.org/articles/what-would-be-the-impact-of-an-ai-boom-on-interest-rates-and-inflation/.

APPENDIX TABLE 1

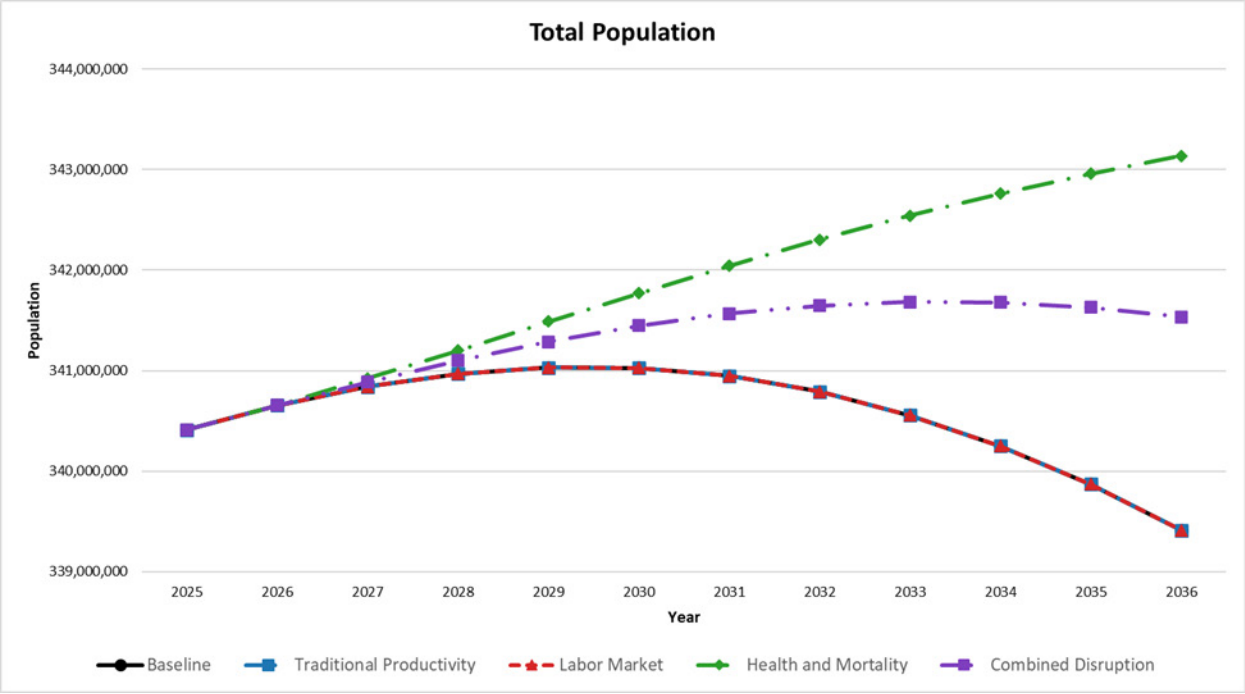
Variability of Key Macro Indicators: Historical and Model Comparison

	Historical Decades (1960 – 2020)						Model Scenarios (2025-2035)				
Indicator	60 – 70	70 – 80	80 – 90	90 – 00	00 – 10	10 – 20	Baseline0	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Labor Productivity	33.29	19.49	16.27	26.64	29.46	16.47	NA (NA)	NA (NA)	NA (NA)	NA (NA)	NA (NA)
Nominal GDP	97.89	166.21	108.70	71.91	46.81	42.04	47.74 (33)	72.11 (50)	61.03 (33)	61.04 (33)	72.11 (50)
Marginal Labor Share	0.61	0.56	0.55	0.58	0.43	0.54	0.54 (17)	0.54 (17)	0.30 (< 0)	0.54 (17)	0.30 (< 0)
Labor Force Participation Rate	0.70	3.20	2.80	0.60	-2.70	-2.80	0.00 (33)	0.00 (33)	-3.00 (< 0)	0.00 (33)	-3.00 (< 0)
Age-Specific Mortality	-0.03	-0.13	-0.08	-0.10	-0.13	0.19	-0.07 (67)	-0.07 (67)	-0.07 (67)	-0.26 (< 0)	-0.18 (< 0)

NOTES: Labor productivity (BLS/FRED: OPHNFB) and nominal GDP (BEA/FRED: GDP) calculated as cumulative geometric growth and expressed as percentages. Marginal labor share (BEA/FRED: COE, GDP) calculated as the sum of yearly changes of compensation to employees divided by the sum of yearly changes to GDP and expressed as proportions. Labor force participation rate (BLS/FRED: CIVPART) calculated as cumulative percentage point change and expressed in percentage points. Age-specific mortality rate (Human Mortality Database: USA Mx_1x1) calculated as the unweighted mean across age groups of each group's cumulative proportional change in central death rate. Numbers in parentheses denote model scenario parameter's percentile within the historical decade distribution for a specific indicator. "< 0" indicates a model parameter's cumulative change falls below the historical distribution.

FIGURE 1

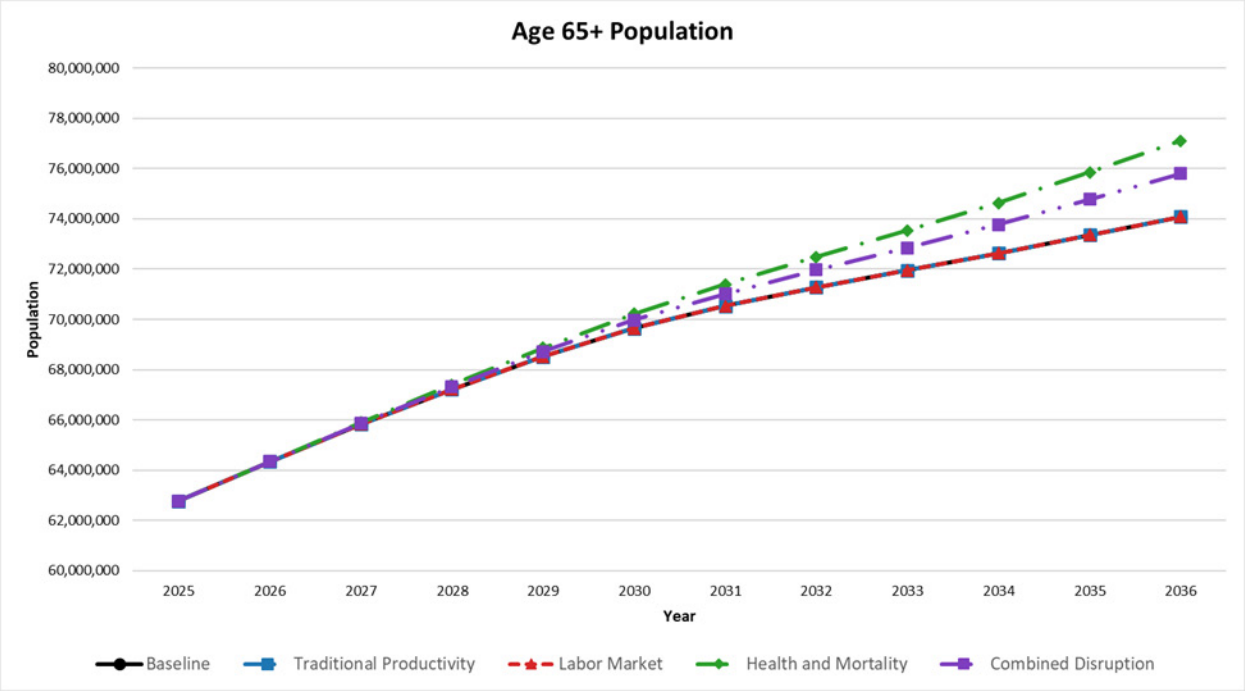
Total Population



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 2

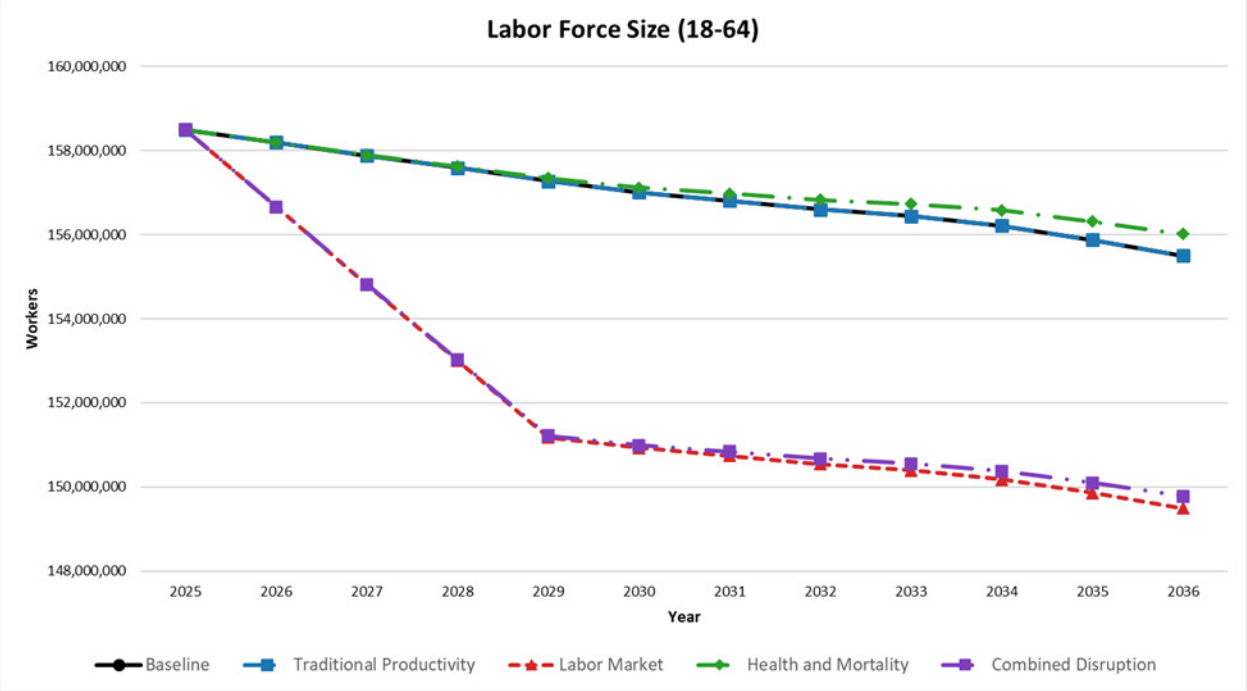
Age 65+ Population



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 3

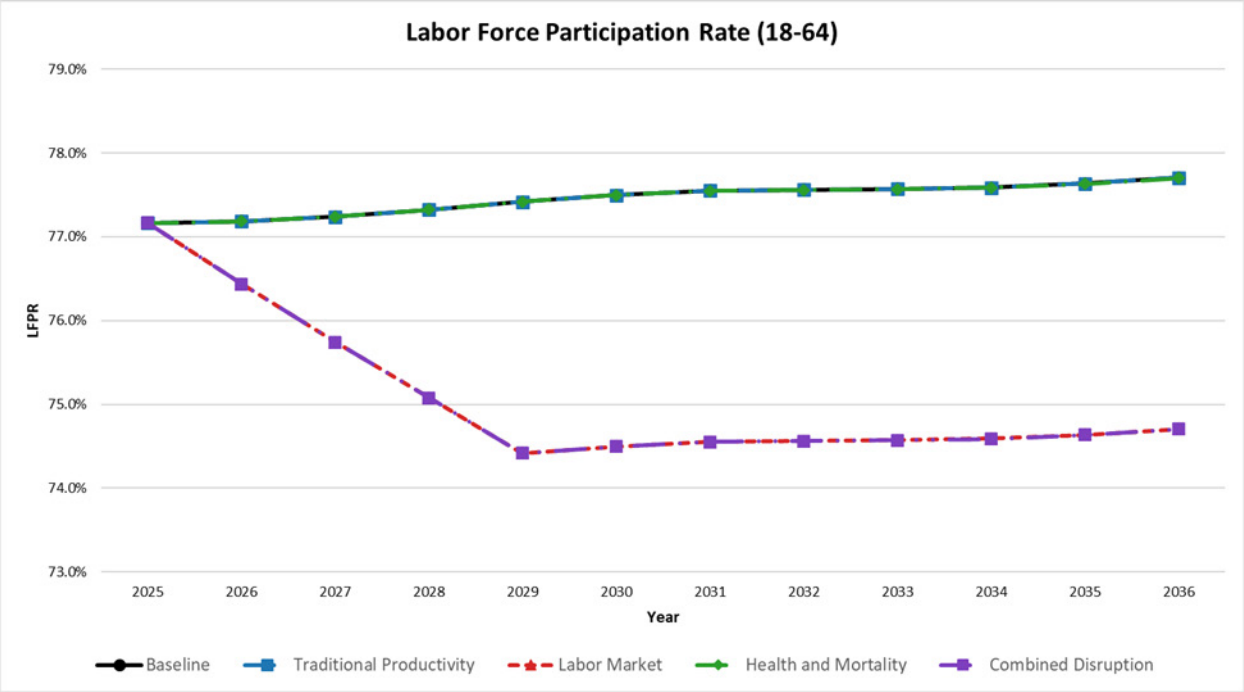
Labor Force Size (18-64)



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 4

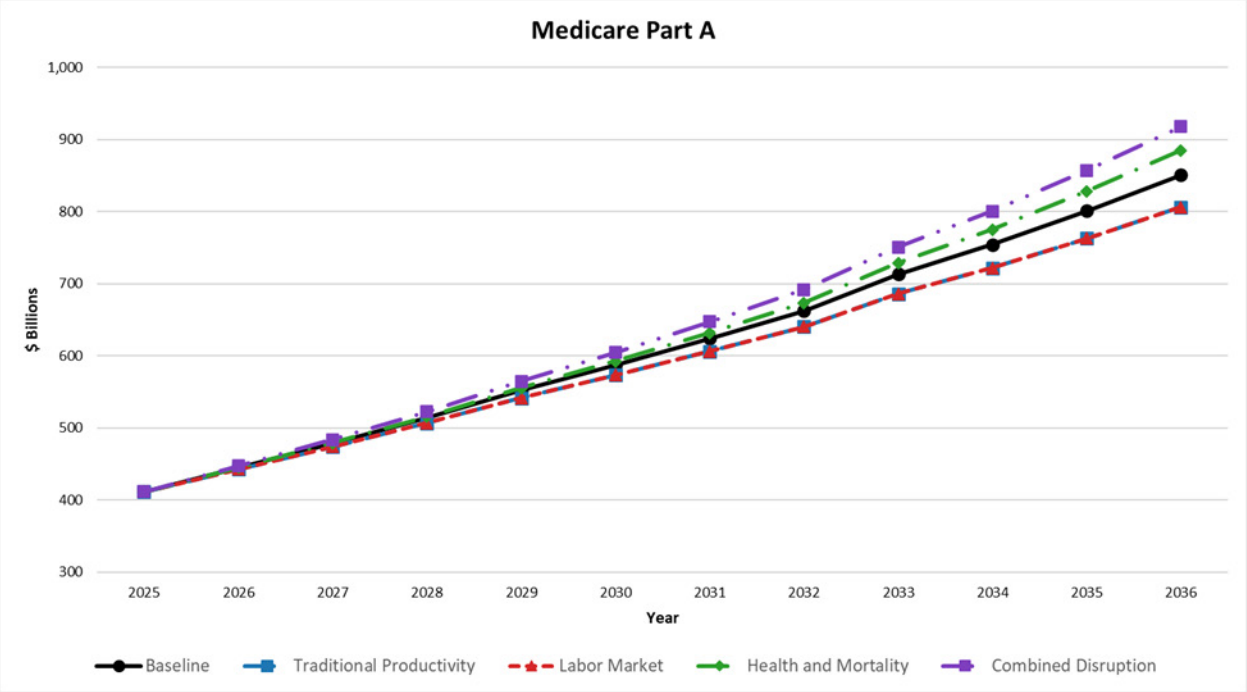
Labor Force Participation Rate (18-64)



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 5

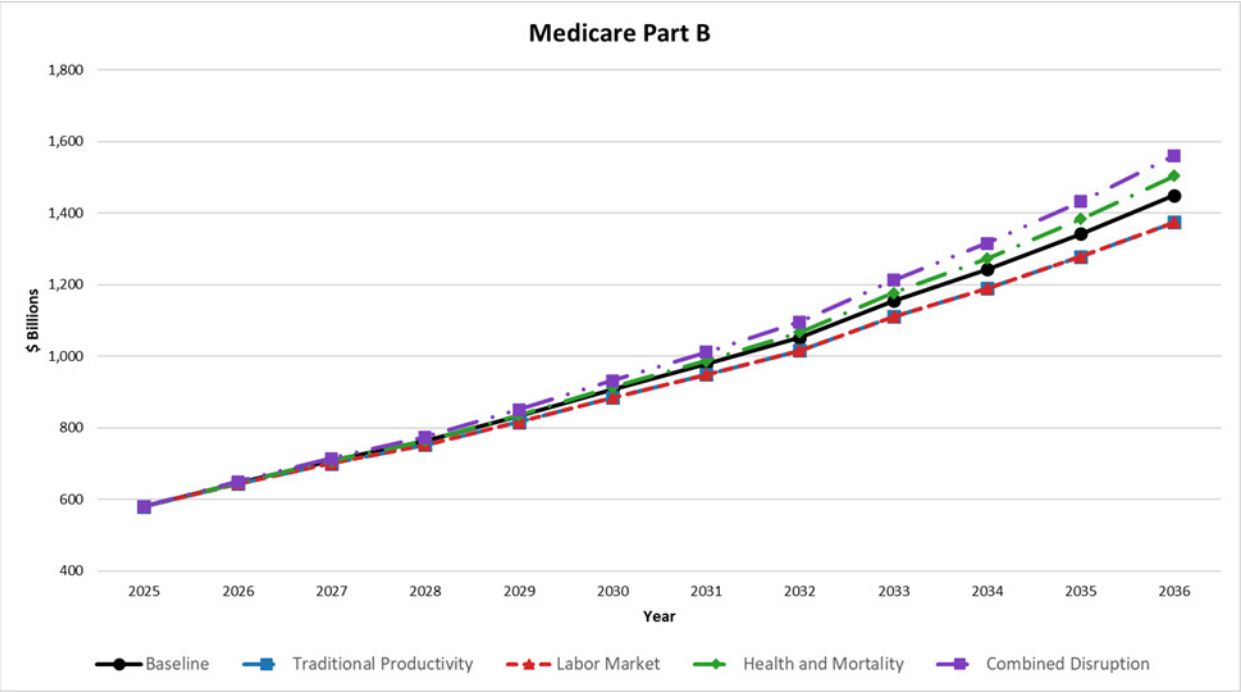
Medicare Part A Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 6

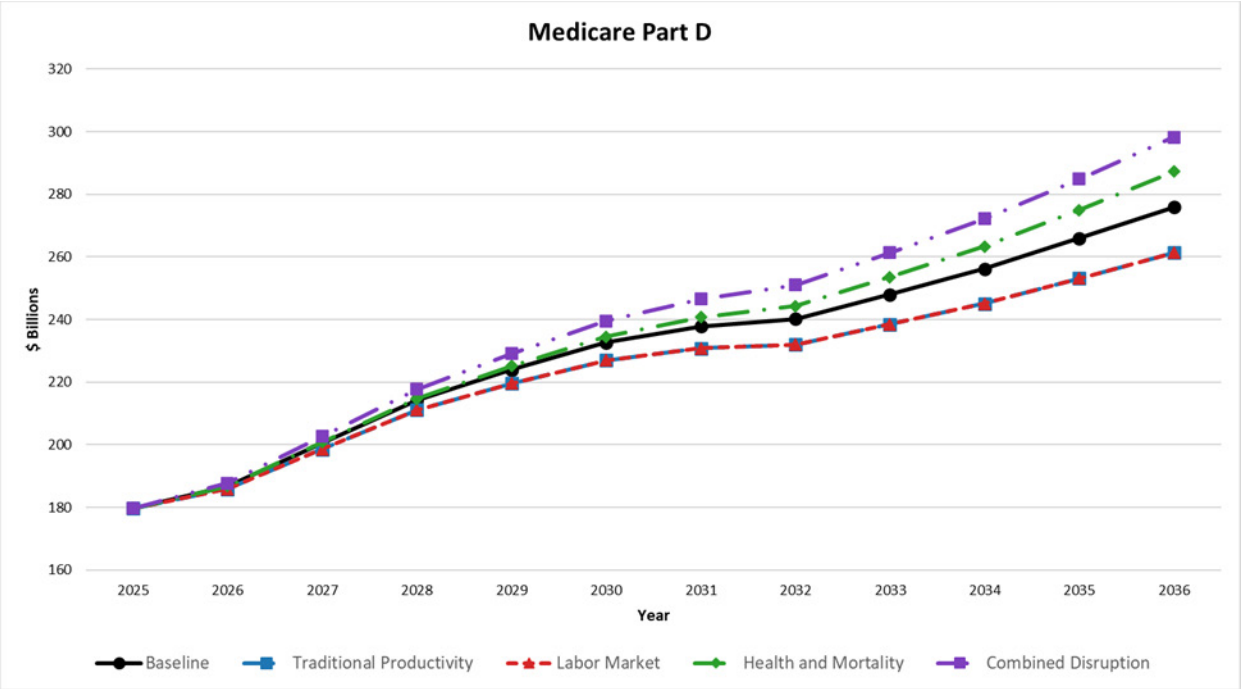
Medicare Part B Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 7

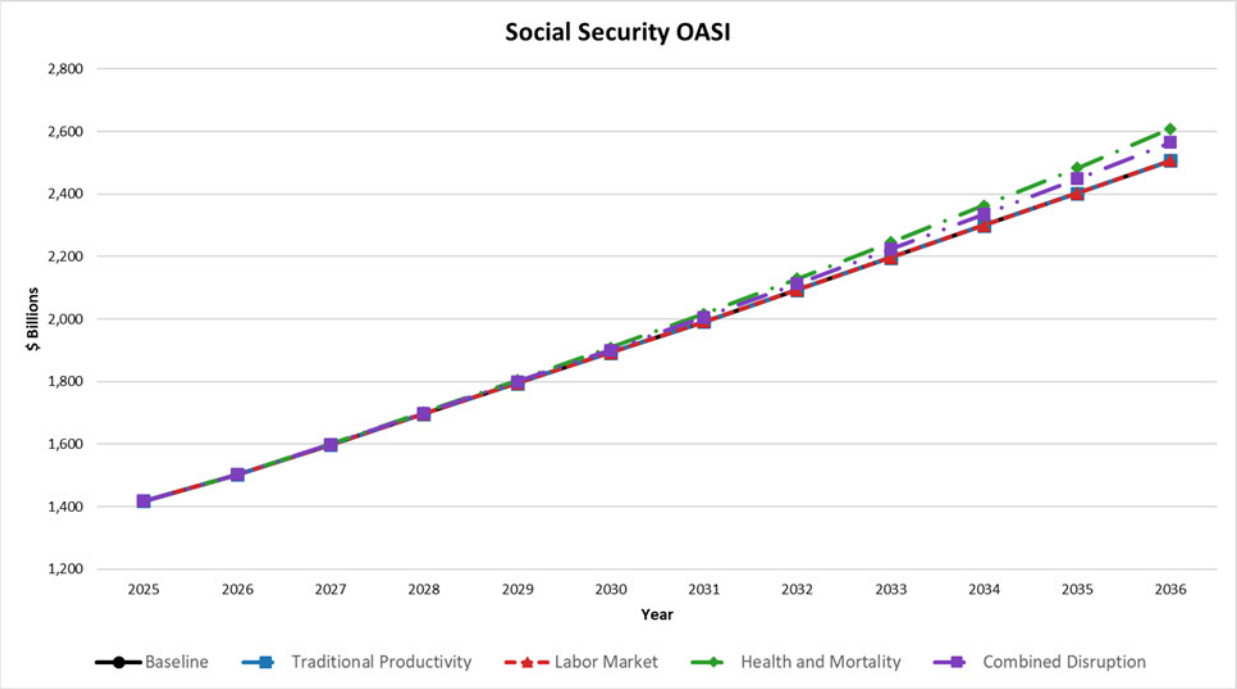
Medicare Part D Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 8

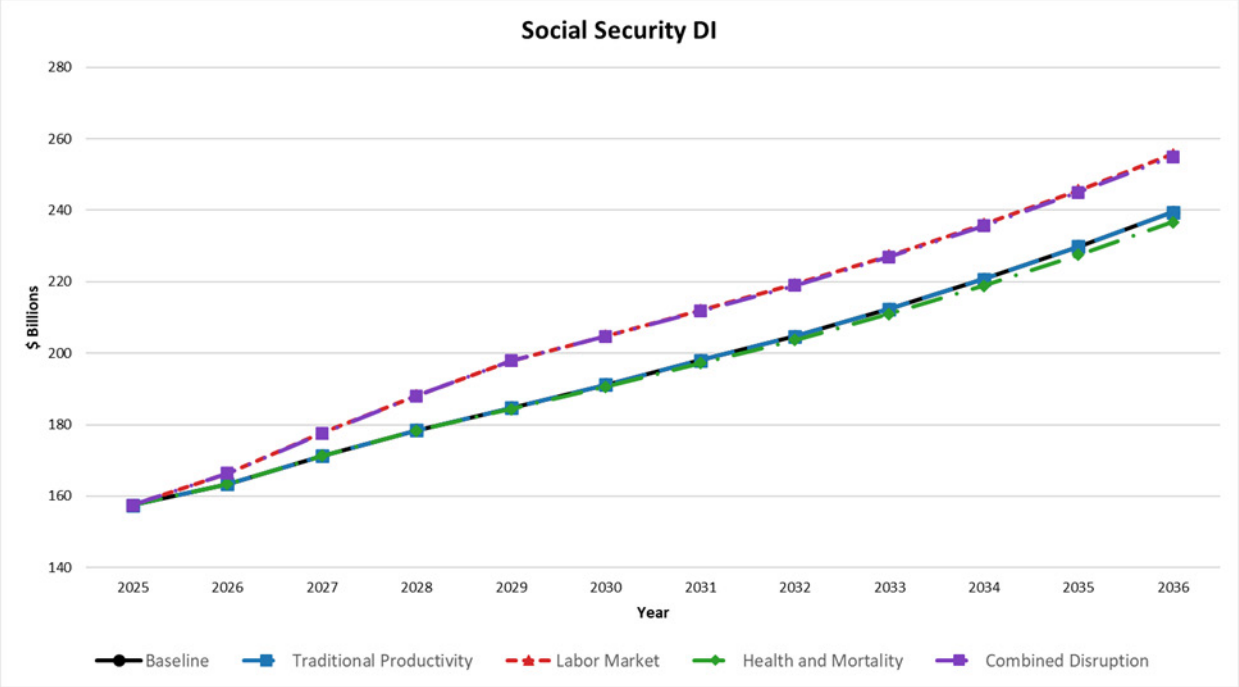
Social Security Old Age and Survivors Insurance Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 9

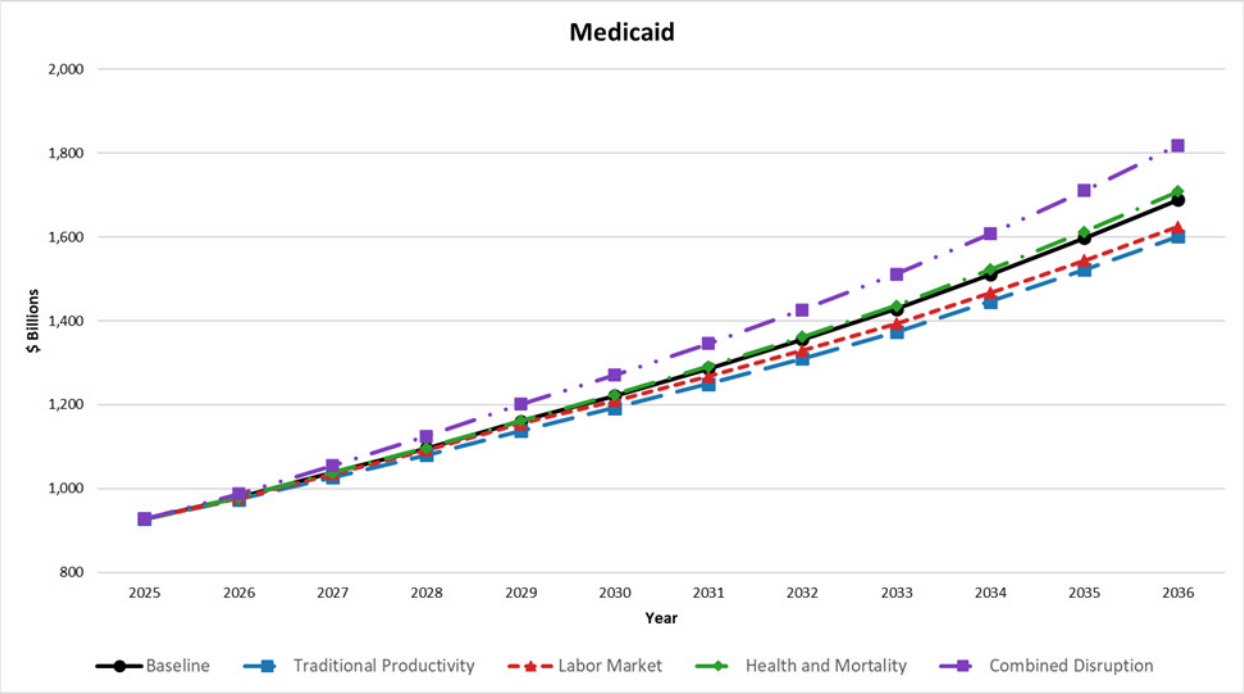
Social Security Disability Insurance Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 10

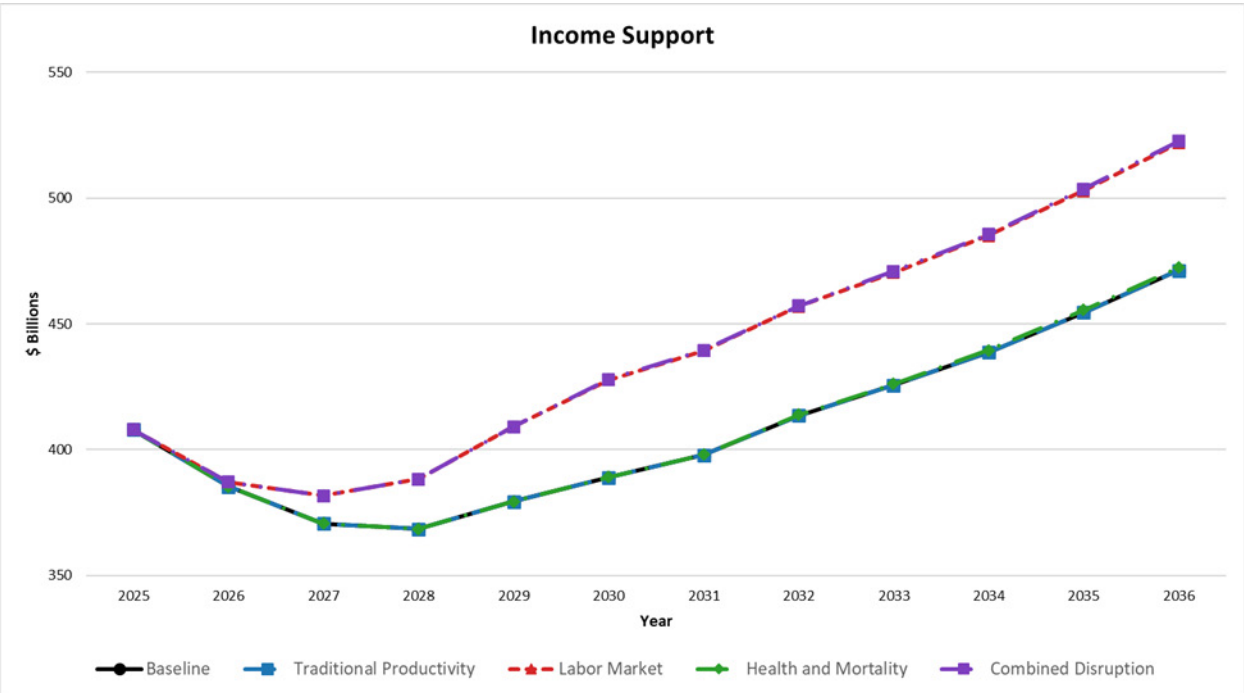
Medicaid Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 11

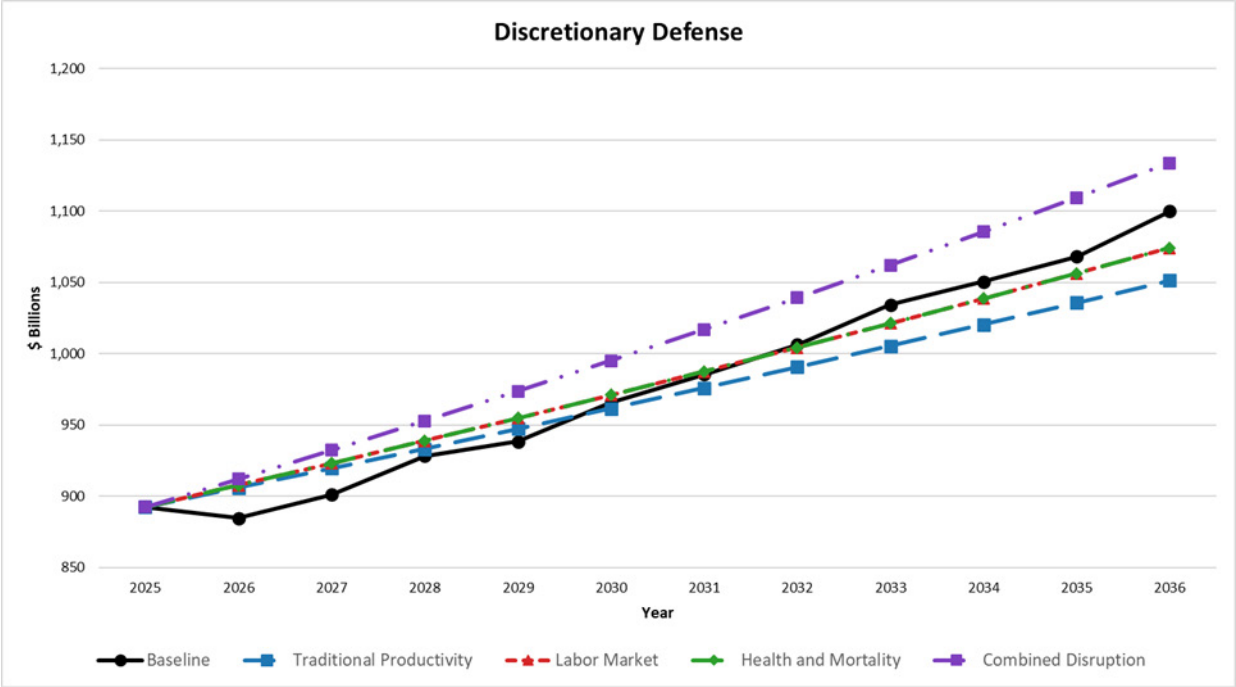
Income Support Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 12

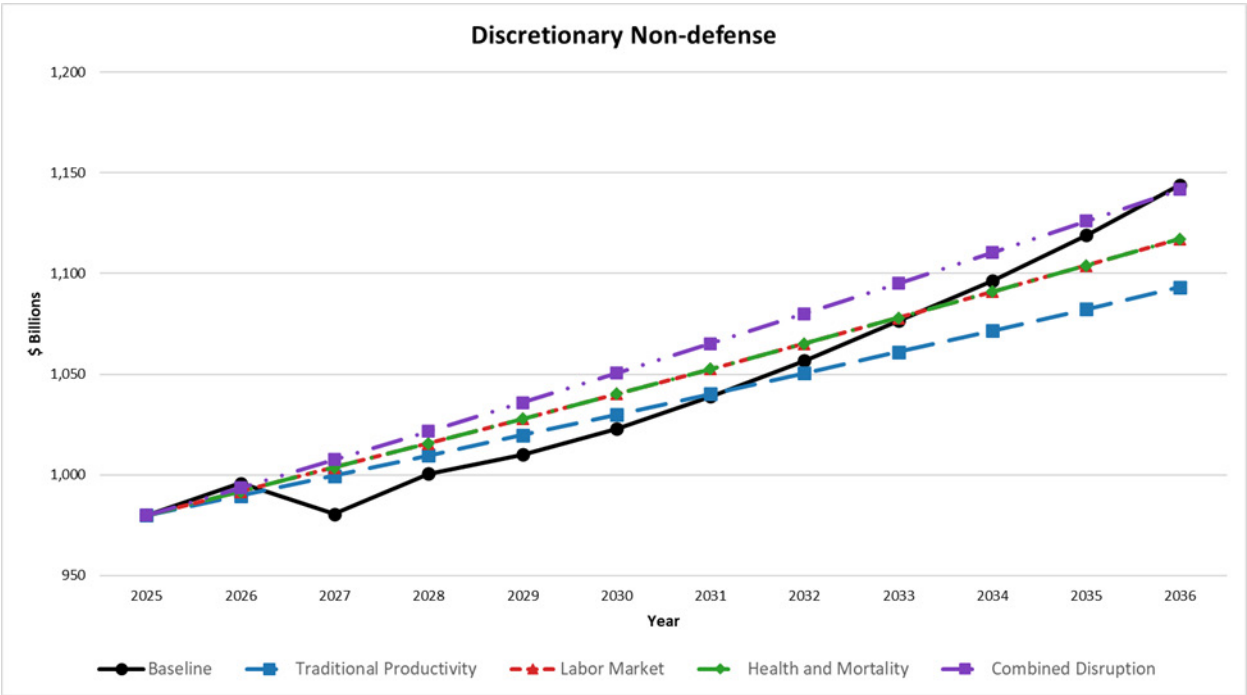
Discretionary Defense Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 13

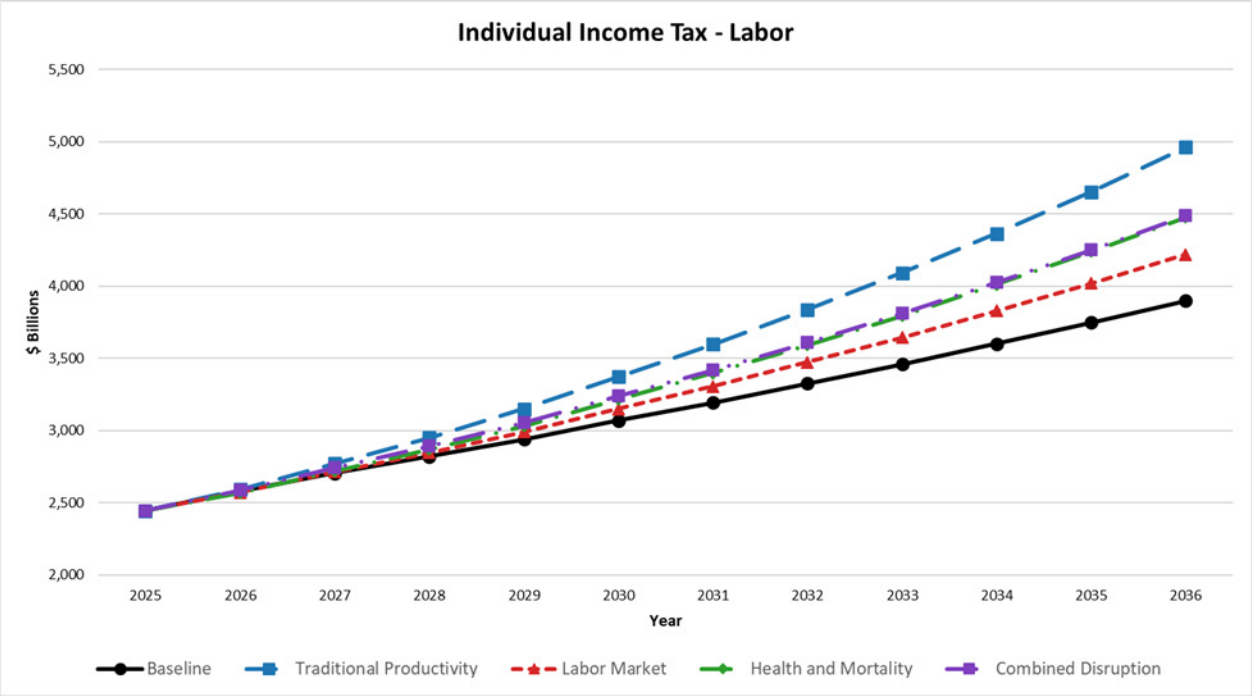
Discretionary Non-defense Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 14

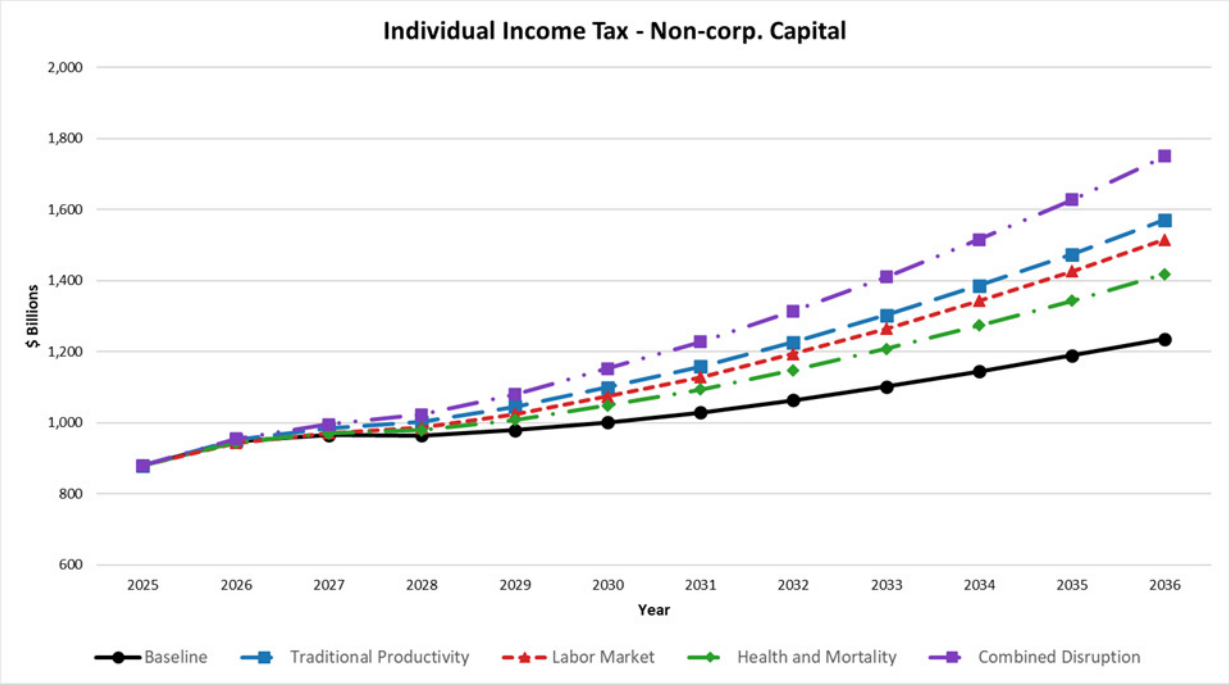
Individual Income Tax Revenues – Labor



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4..

FIGURE 15

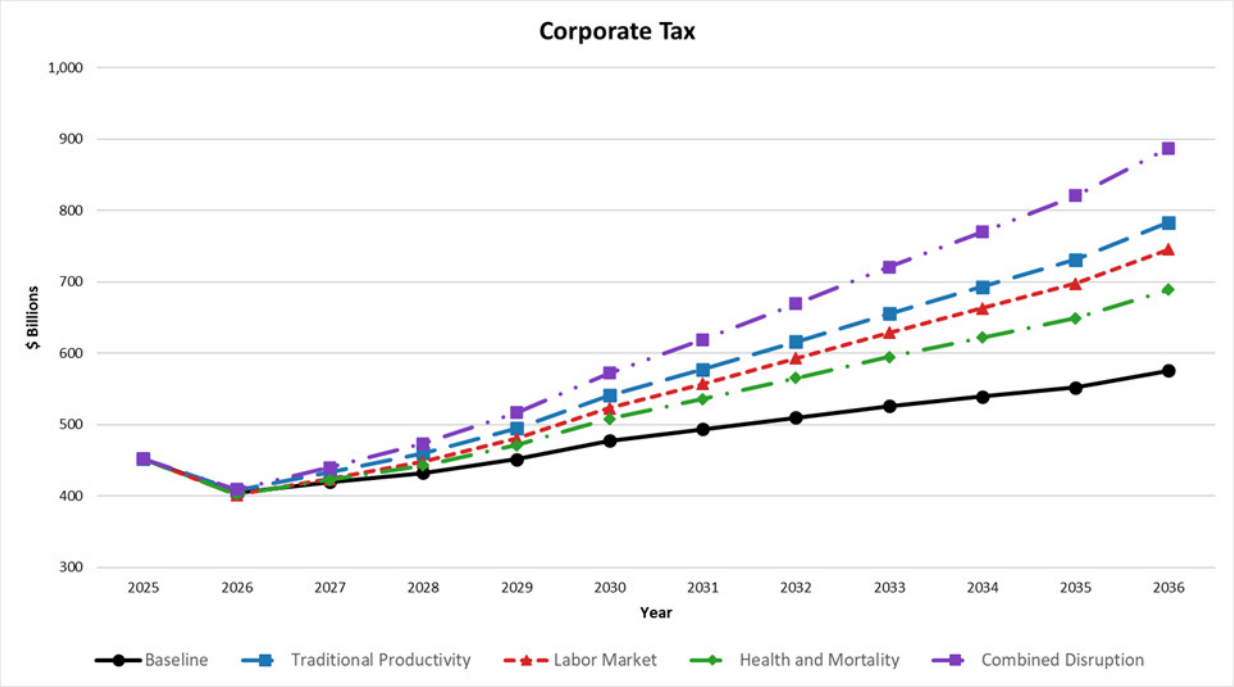
Individual Income Tax Revenues – Non-corporate Capital



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 16

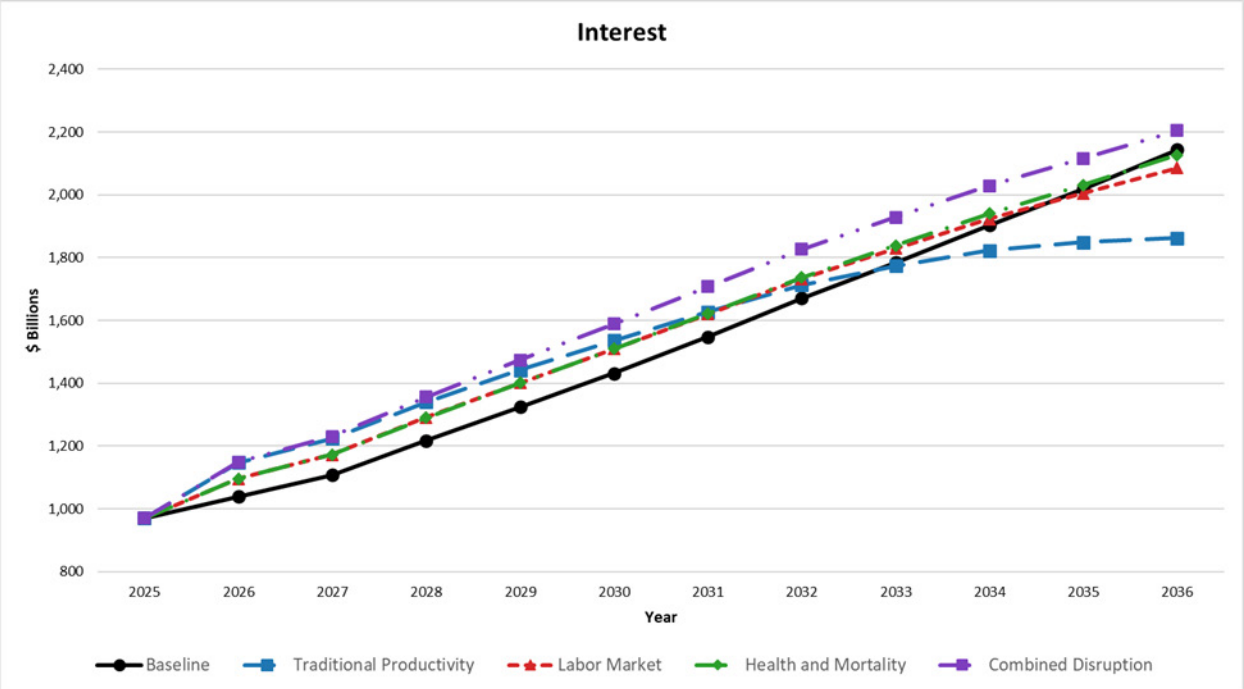
Corporate Tax Revenues



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 17

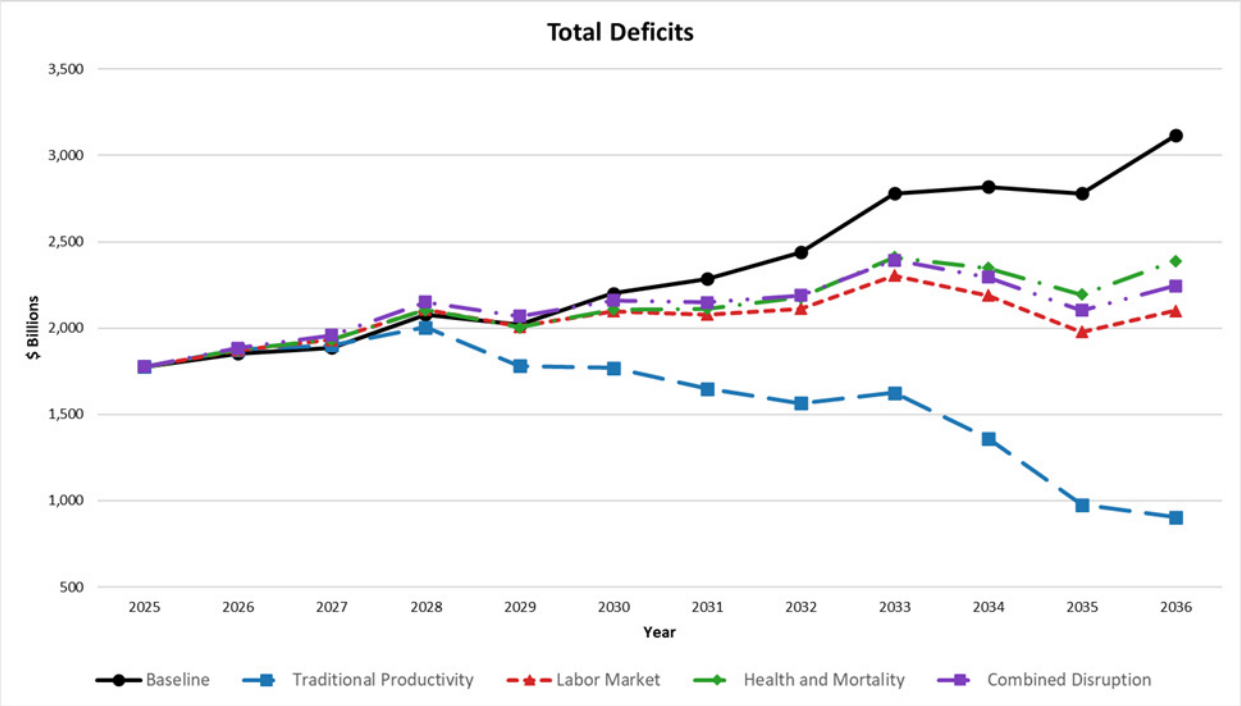
Interest Outlays



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 18

Total Deficits



NOTE: Traditonal Productivity corresponds to scenario 1; labor market corresponds to scenario 2, health and mortality corresponds to scenario 3, and combined disruption corresponds to scenario 4.

FIGURE 19

Total Deficits as a Percentage of GDP

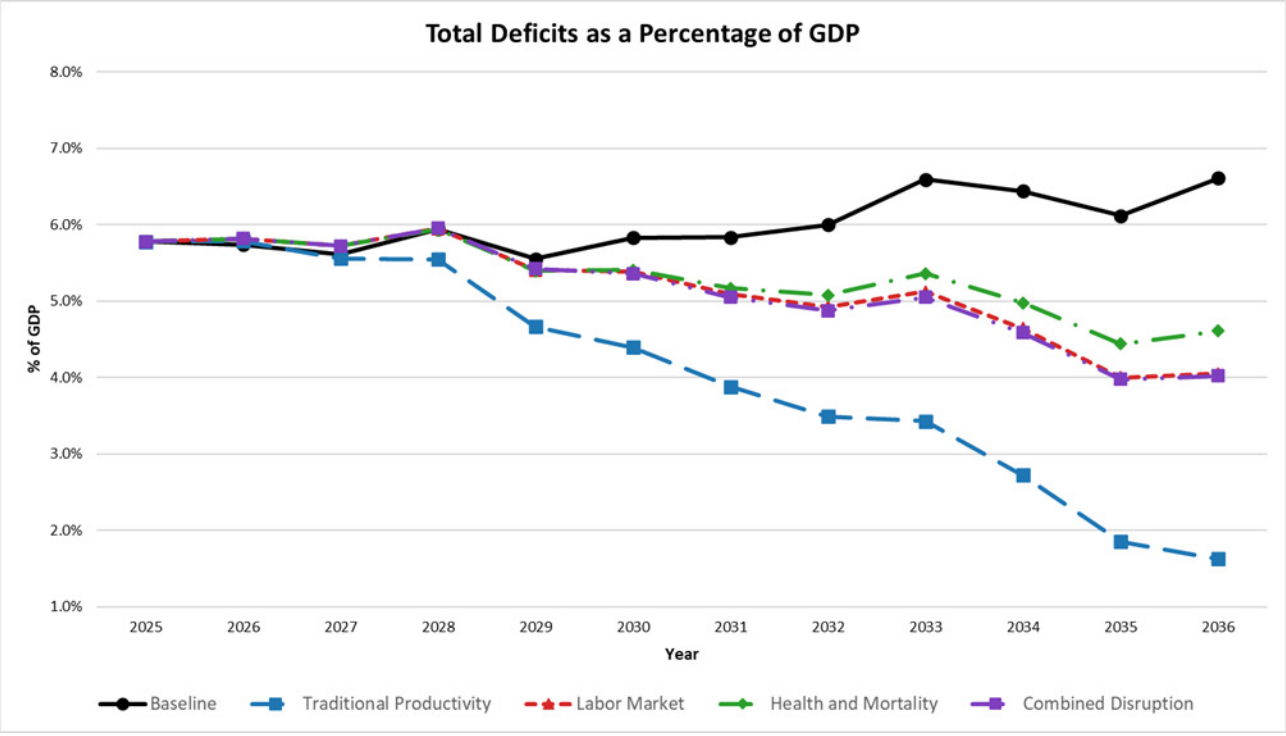


FIGURE 20

Baseline Total Deficits by Primary Deficits and Interest Costs

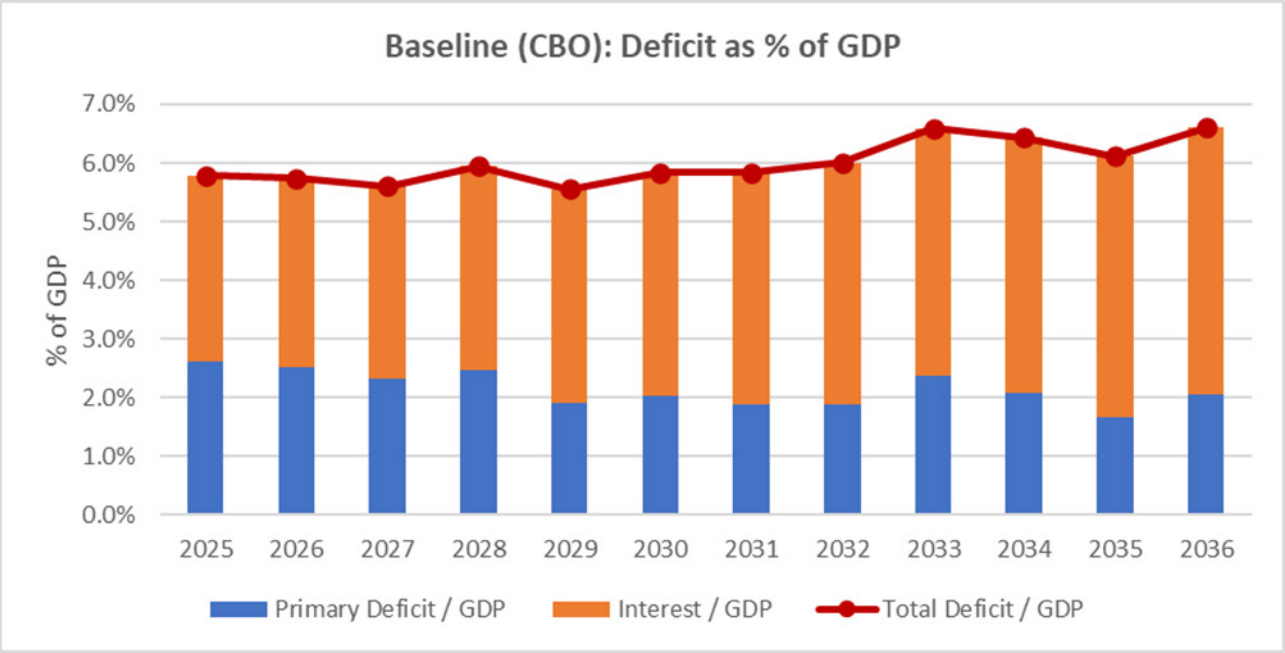


FIGURE 21

Scenario 1 - Total Deficits by Primary Deficits and Interest Costs

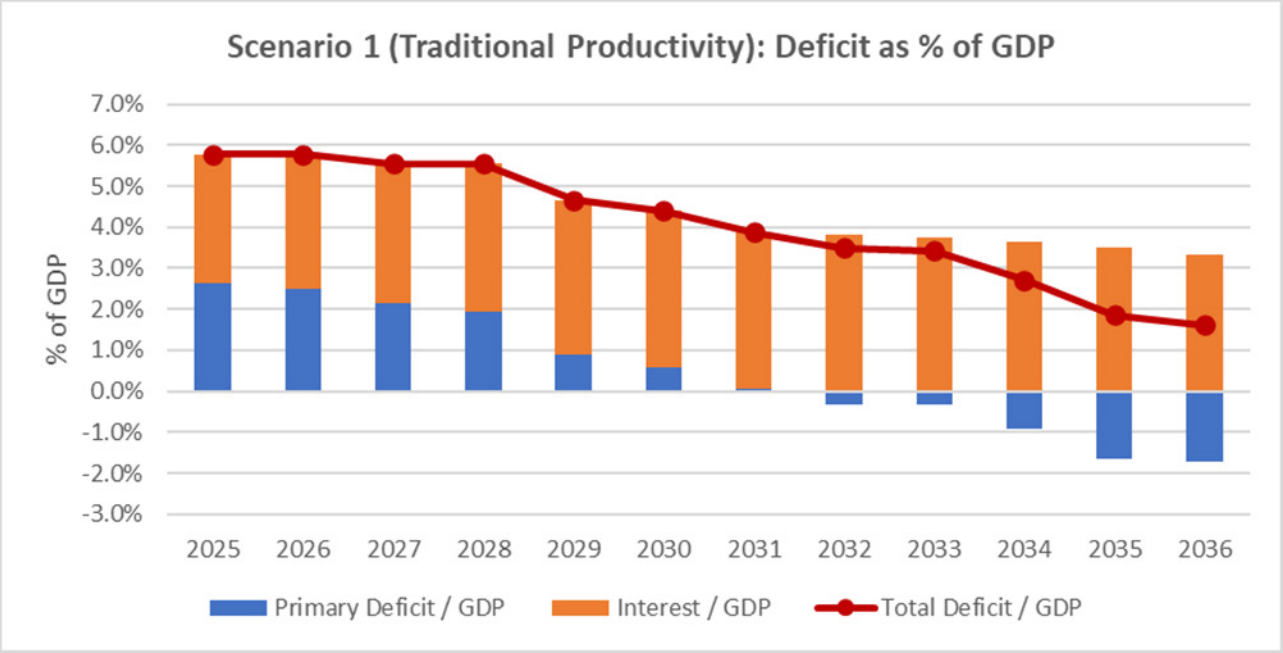


FIGURE 22

Scenario 2 - Total Deficits by Primary Deficits and Interest Costs

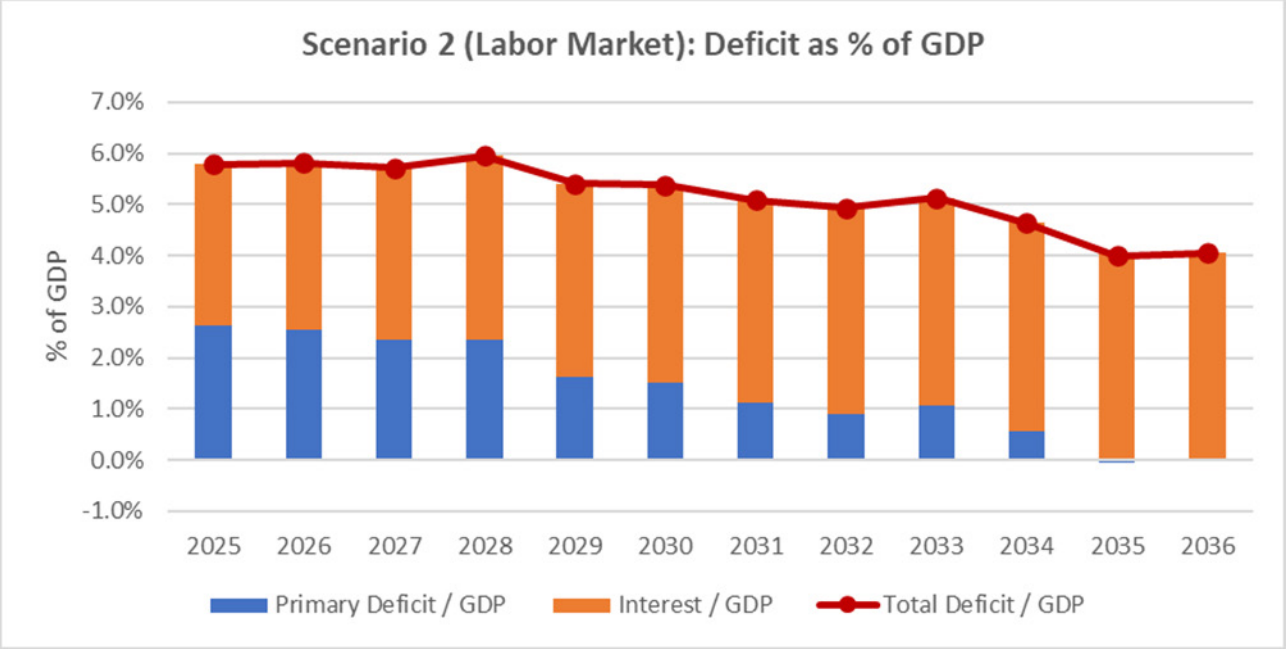


FIGURE 23

Scenario 3 - Total Deficits by Primary Deficits and Interest Costs

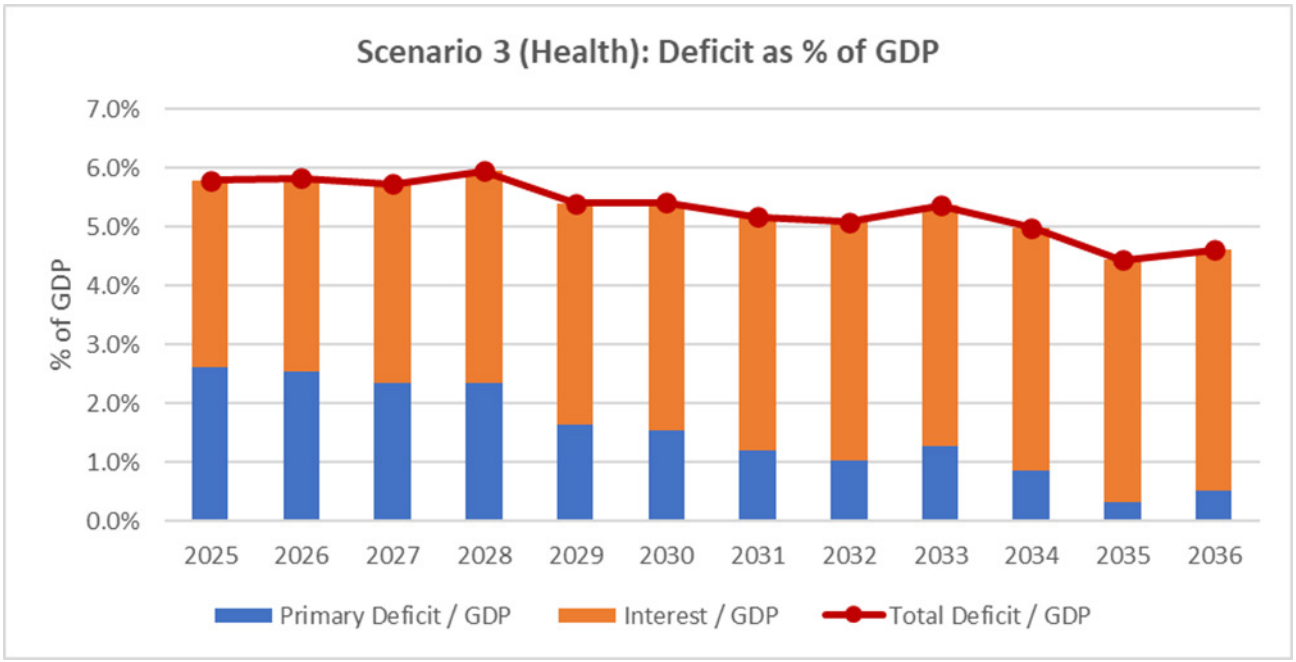


FIGURE 24

Scenario 4 - Total Deficits by Primary Deficits and Interest Costs

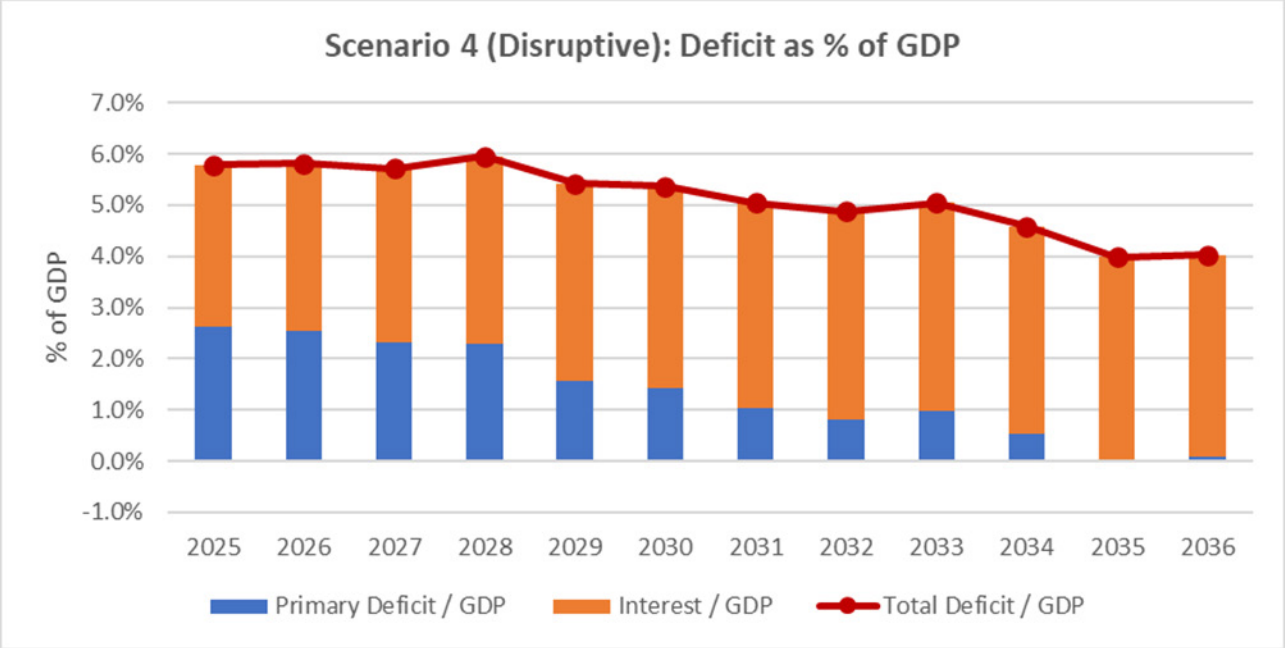


FIGURE 25

Scenario 1 - Sensitivity Analysis

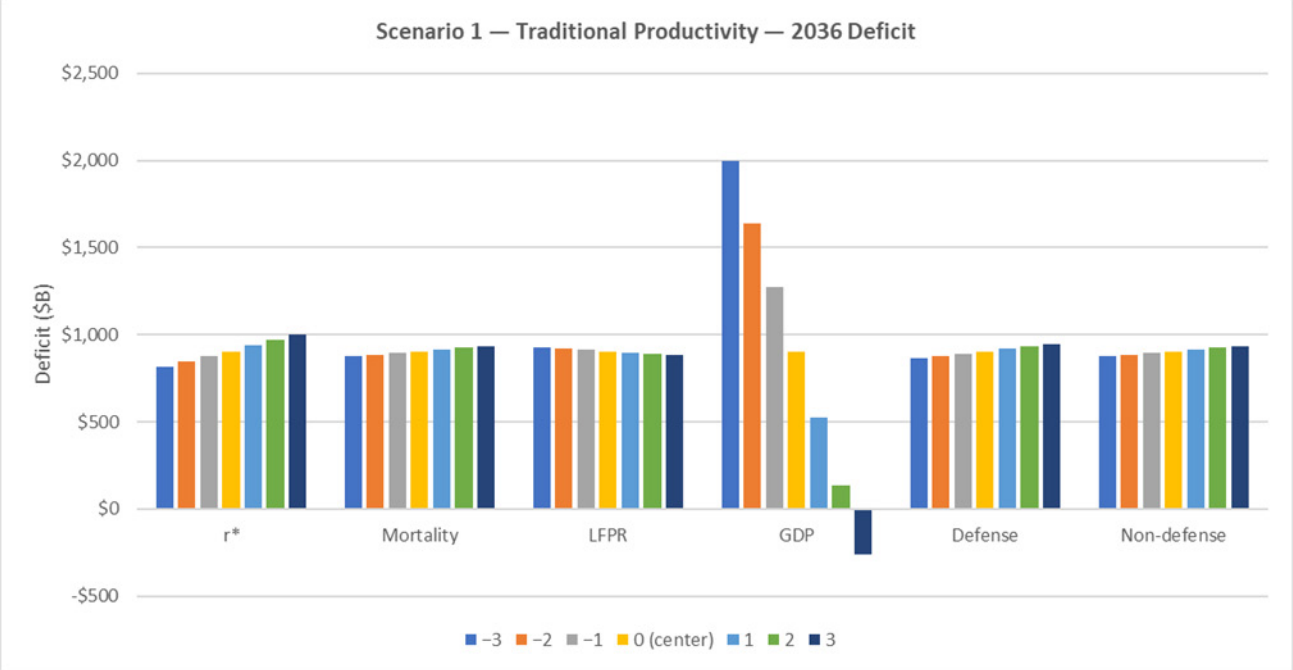


FIGURE 26

Scenario 2 - Sensitivity Analysis

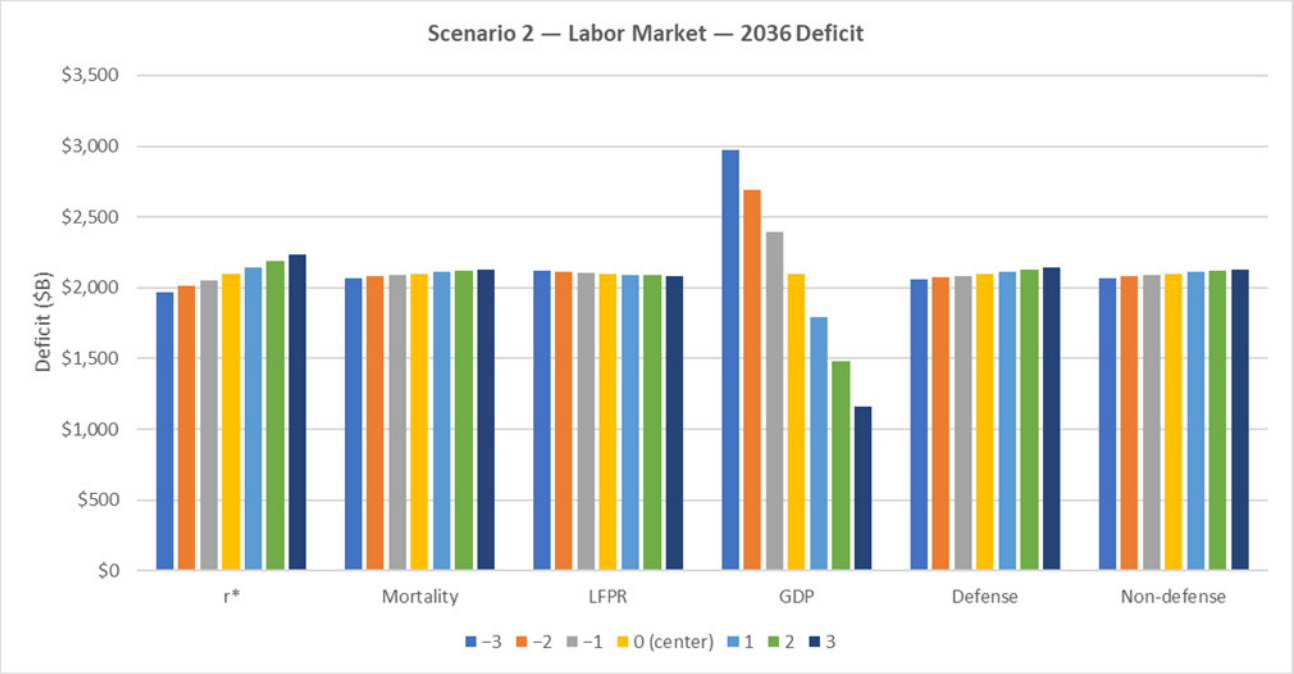


FIGURE 27

Scenario 3 - Sensitivity Analysis

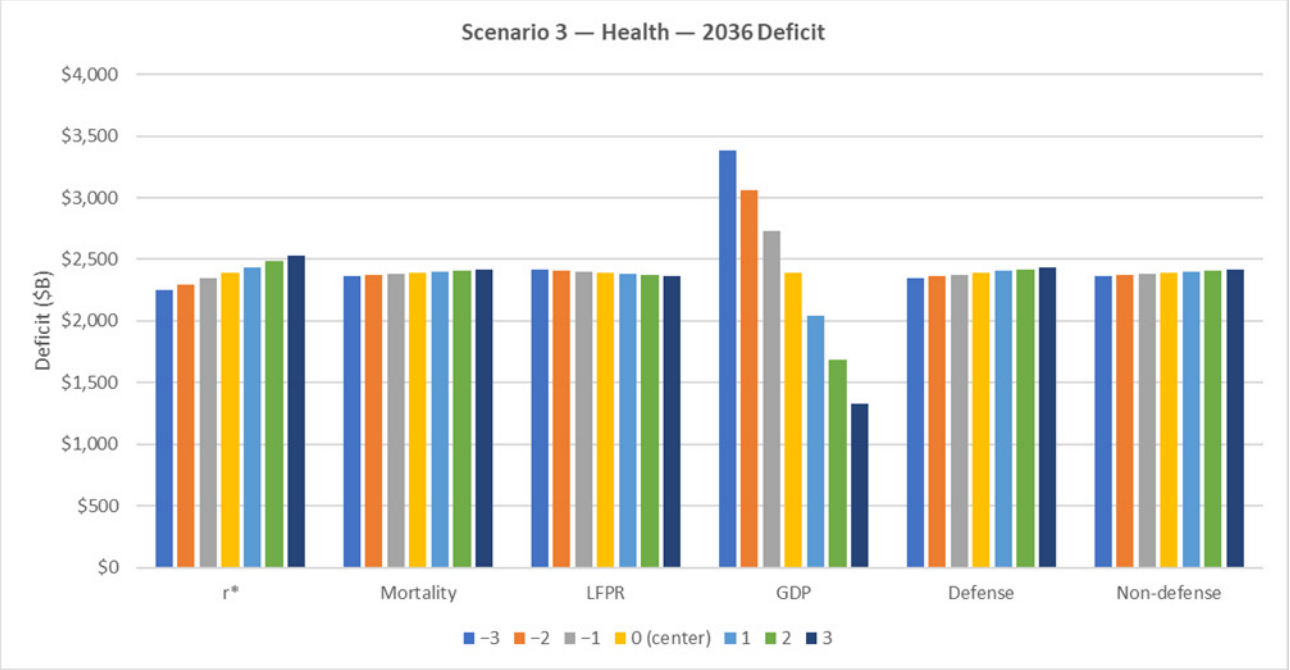
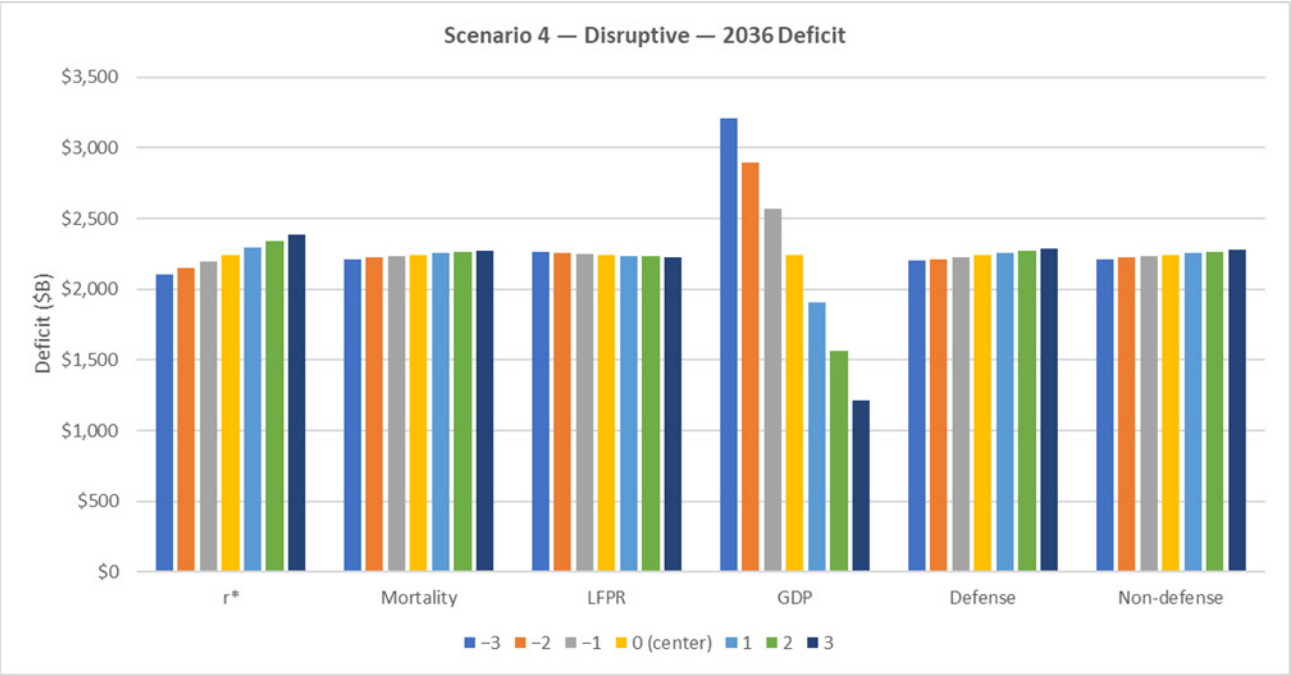


FIGURE 28

Scenario 4 - Sensitivity Analysis



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