PREDISTRIBUTION INITIATIVE

Predistribution AI Lab Discussion Paper Series – Part I

Modeling Ghost GDP:

Macro-financial Risk and Diversified Portfolios in the Age of Artificial Intelligence, Automation, and Populism

Prepared by

The Predistribution Initiative (PDI)

With the support of Anthropic's Claude

June 2026

Working Draft

Introducing the Predistribution AI Lab Discussion Paper Series

The Predistribution Initiative's (PDI) AI Lab discussion paper series:

- Models the macro-financial risks of labor displacement driven by Artificial Intelligence (AI) and automation (collectively referred to in the series as AI);
- Considers safety and cognitive risks posed by AI under current corporate governance models;
- Proposes predistributive interventions that could prevent declines in incomes, safety risks, and cognitive issues from becoming systemic crises; and,
- Offers a specific prototype to be refined and adapted across numerous contexts.

Part I of the discussion paper series (this first paper) analyzes four scenarios, modeling the cascading effects of income erosion and unemployment on consumption, tax revenue, mortgage markets, corporate debt, equity values, pension systems, and insurance assets. Scenarios are designed to illuminate key transmission channels of potential macro-financial risk through the real economy, markets, and to diversified investment portfolios. Three scenarios are based on higher unemployment numbers as predicted by Anthropic CEO, Dario Amodei, while the "lighter" scenario is built on the historical precedent of declining returns to labor and a "fissured workplace" even as employment has grown with technology.

We do not take a view on whether AI will lead to higher unemployment. Rather, we center our attention on the risks of historical and ongoing declining returns to labor that are shared across stakeholders in society, including financial risks to diversified investors' portfolios. We argue that the advent of AI is an inflection point at which the world is either poised to deepen the current trends toward risk, or at which we can sculpt and refine economic structures to avoid such risks. This first paper primarily focuses on macro-financial analysis. However, safety, blind spots, and cognitive bias risks are also considered, particularly in Part II of the discussion paper series.

Part II (the second paper) offers practical models for addressing such risks, particularly via broadening equity-linked compensation and corporate governance participation to include workers, communities, and content creators who take risk and create value alongside executives and investors in the production process. The report further contextualizes the current technological transition in the broader backdrop of decades of declining returns to labor versus capital, depreciating cash relative to appreciating asset values, and corporate governance that is more strongly oriented toward shareholders versus other corporate stakeholders.

At the core of Part II is a recognition that the economy and productivity have been advanced in recent history through the contributions of workers (formally and informally employed, collectively "human capital"), communities who host infrastructure and natural resources projects (collectively "social capital"), and content creators and others who provide data which has advanced technology (a mix of

human and social capital). However, with financial capital being prioritized by corporate governance over human, social, and natural capital, these other stakeholders have not been compensated in a manner that keeps pace with financial capital, resulting in rising economic inequality, misalignment of incentives across stakeholder groups, disenfranchisement, loss of trust in institutions, polarization, and domestic and geopolitical conflict.

Without reform to status quo economic and market structures, AI is poised to accelerate and deepen these trends. One of our central findings is that the timing of predistributive mechanisms is critical. In the context of the workforce for instance, workers who hold stakes in companies adopting productivity-enhancing technology—regardless of whether their roles will be eliminated—can be rewarded for the value they have created via participation in the gains, be incentivized and motivated to contribute to technological advancements, and sustain the aggregate demand upon which the economy and financial portfolios depend.

Part III (the third paper) offers a specific prototype of an intervention designed for rideshare drivers in the context of autonomous vehicles (AVs). A three-pillar structure is proposed to offer ongoing cash incomes, equity participation in AV platforms, and diversified investment accounts to displaced and working drivers. The model offers foundational proposals to be further refined with stakeholders and can be adapted to other contexts, including communities hosting infrastructure and natural resource projects, and content creators whose intellectual, creative, and personal capital is being used to train AI.

We highlight the importance of living wages (incomes) for those who continue to work, as well as freedom of association and collective bargaining. We also compare the proposals we offer to those already on the table, from universal basic income (UBI), to sovereign wealth funds (SWFs), to purpose trusts and beyond, and evaluate pros and cons of various approaches.

Ultimately, these discussion papers shape the beginning of a series considering where economic and financial structures have fallen short, and where they can improve. The Predistribution AI Lab is being shaped as a forum for further co-creation, and we hope readers will join us in refining and building on the ideas through this community of practice.

Context

AI is poised to transform the global economy at unprecedented speed. Predictions abound about whether this emergent technology will lead to mass job creation or destruction over varying periods of time. Leading AI executives, such as Anthropic CEO Dario Amodei, project that AI could drive GDP growth of 5 to 20% annually while simultaneously leading to 10 to 20% unemployment. In February, financial analyst James Van Geelen of Citrini Research published a widely circulated scenario describing what this trajectory might actually look like: white-collar workers downshifting into gig economy roles, consumer spending collapsing, and "Ghost GDP," or economic output that appears in national accounts but never circulates through the human consumer economy. The piece moved stock prices and continues to be discussed widely in the media, social media, and prediction markets.

Whether or not such predictions turn out to be accurate, they raise critical questions that demand thoughtful scenario planning. This discussion paper takes a further step in that process—with explicit mathematical modeling of potential displacement scenarios calibrated to Bureau of Labor Statistics (BLS), Federal Reserve data, and Global Financial Crisis (GFC) benchmarks. We consider resulting consumption gaps and examine how these dynamics affect pension funds, insurance liabilities, and sovereign fiscal positions through various transmission channels of macro-financial risk. Scenarios consider the historical precedent of technology leading to more jobs, albeit many of lower quality.

Under mass displacement scenarios, even AI companies' own revenue streams—enterprise software, consumer subscriptions, advertising—face material contraction, creating a powerful alignment of interest between the AI sector and broader economic stability. Most importantly, we consider structural conditions which can help navigate risks foreseen by the likes of Amodei to ensure markets and society benefit from this incredible technology. While the discussion paper primarily focuses on systemic economic and market risks stemming from potential declines in aggregate consumption, we also consider AI safety risks and governance models that can help avoid them.

The central concepts that follow from this paper are straightforward, and we elaborate on them in Parts II and III of the *Beyond Ghost GDP* discussion paper series. Predistribution means structuring the economy for broad-based prosperity and participation, so that it can sustain itself and not collapse under the pressures of market concentration. We evaluate mechanisms like employee ownership, community ownership of AI infrastructure, and equity-linked compensation for content creators and others who generate value for AI systems—rather than concentrating wealth first and attempting to redistribute it through taxes and transfers after the fact. We also consider literature and best practices relating to complex systems, recognizing that top-down approaches to managing and governing such systems, like societies, are bound to fail. When considering AI safety and mechanisms to ensure it benefits everyone, there is significant value to broadening participation of workers, communities, and consumers in corporate governance mechanisms, supported by robust training and onboarding programs.

Redistribution refers to traditional mechanisms like taxation and government spending programs, including universal basic income (UBI) and a centralized Sovereign Wealth Fund (SWF). We find that redistribution alone, in the forms currently being discussed, covers only a small fraction of the projected income shortfall in the Amodei and Citrini Research scenarios and/or leaves society vulnerable to the concentrated power dynamics Amodei foresees. In concentrated markets and societies, those who have wealth and power are positioned to leverage their own worldviews and theories of change to determine the quantum and terms of redistribution, where investment flows in society, how policies are structured, and how AI models are trained. Predistributive approaches are not only more effective economically but also more empowering for the people they serve and more durable from a political and societal perspective.

The Citrini's research Ghost GDP threat and variations of it are real. And AI safety risks are worth taking seriously. But these scenarios are not inevitable. They are the predictable consequence of specific ownership and governance structures—those in which the productivity gains from technological advances have accrued narrowly while the displacement costs are increasingly broad. Change that structure, and the economics and real world outcomes change with it. This discussion paper series offers an analytical foundation for understanding how.

An important contextual note on our approach and design: This discussion paper offers analysis and customizable scenarios to be workshopped further, not prescriptions. Our goal is to catalyze a serious conversation among business leaders, investors, policymakers, and the public about how predistributive approaches—broad-based equity-linked compensation for workers and communities ("BEC" models) and broadening corporate governance participation ("BCGP" models)—can mitigate potential systemic risks of AI before those risks become unmanageable. It is also focused on the US to maintain a manageable scope for modeling scenarios. Following the publication of this report we welcome the opportunity to engage with stakeholders to continue to test assumptions, methodologies, and scenarios to ensure the research contributes to robust solutions for markets and society in the US and globally.

Executive Summary

This report models the potential systemic financial consequences of AI-driven labor market disruption in the US. It traces how workforce displacement and employment degradation could propagate through consumption, credit, equity, pension, insurance, and fiscal channels—producing cascading losses that scale dramatically with the severity of displacement. The analysis is built around four scenarios, ranging from a Light scenario (no net job losses, but widespread reclassification of workers into precarious gig employment) to an Aggressive scenario (20% unemployment), calibrated to projections by Anthropic CEO Dario Amodei and others. The model is anchored to Bureau of Labor Statistics (BLS) data, Federal Reserve data, and empirical benchmarks from the 2008-2010 Global Financial Crisis (GFC).

A central finding is that even in the absence of net job losses, the structural degradation of employment—the shift of approximately 16 million workers from salaried positions to gig and contract arrangements—produces meaningful macroeconomic drag, reducing GDP by roughly 1%. This channel is invisible to headline unemployment statistics but generates material income losses, benefit elimination, and cascading effects on household debt service, retirement contributions, and tax revenue. As displacement intensifies across the Moderate, High, and Aggressive scenarios, the financial transmission channels interact and amplify one another, producing total economy-wide value at risk ranging from approximately $15–18 trillion in the Light scenario to $62–72 trillion in the Aggressive scenario.

Key Findings

Table 1: Displacement Scenarios and Macroeconomic Impact

Scenario (unemployment rate)	Light (4.4%)	Moderate (10%)	High (15%)	Aggressive (20%)
Workers displaced	0	8.9M	16.8M	24.7M
Workers shifted to gig status	15.8M	10.5M	7.1M	4.0M
Total workers at risk	15.8M	19.3M	23.9M	28.7M
Annual income lost	$161B	$745B	$1.3T	$1.8T
Total consumption loss	$256B	$1.2T	$2.0T	$2.8T
% of GDP	0.8%	3.9%	6.6%	9.1%
Estimated GDP contraction	1.0%	4.8%	8.1%	11.2%

Across all channels, total value at risk scales dramatically with displacement severity. For comparison, the GFC—triggered by roughly $1.3 trillion in distressed subprime mortgage exposure—nearly collapsed the global financial system. Even the light scenario represents distressed exposure an order of magnitude larger.

Table 2: Economy-Wide Value at Risk by Transmission Channel

Channel	Exposure	Light	Moderate	High	Aggressive
Mortgage defaults	$13.2T	$94–108B	$289–293B	$387–464B	$486–678B
Consumer debt defaults	$4.6T	$39–45B	$111–123B	$177–194B	$245–284B
Corporate debt defaults	$14.1T	$283B	$517–541B	$665–751B	$920B–1.1T
Corporate bond MTM—spread widening	$11.5T	$795B	$2.6–2.8T	$2.6–3.2T	$2.5–3.8T
Equity market decline	$69T	$13.6–17.2T	$41.3–42.0T	$49.2–57.7T	$57.4–66.0T
Social Security	$2.72T reserves	0–1 yr earlier	1–2 yr earlier	2–3 yr earlier	3–5 yr earlier
Tax revenue decline	~$5.2T baseline	–2.6%	–8.0%	–12.8%	–17.4%
Total economy-wide value at risk		~$15–18T	~$45–46T	~$53–62T	~$62–72T

Total economy-wide value at risk is the sum of mortgage defaults, consumer debt defaults, corporate debt defaults, corporate bond mark-to-market (MTM) losses, and equity market decline. Social Security acceleration and tax revenue decline are shown as contextual indicators but are not included in the dollar total.

The losses above are borne by a wide range of investors—banks, mutual funds, ETFs, pension funds, insurance companies, retail investors, and foreign holders. Two categories of institutional investors are particularly important because of their systemic role and the scale of their exposure:

Table 3: Key Investor Portfolio Impairment

Investor Category	Total Assets at Risk	Light	Moderate	High	Aggressive
Pension/retirement	$49.1T	$5.6–7.2T	$17.0–17.6T	$20.4–24.2T	$23.9–27.9T
Insurance	$9.0T	$427–608B	$1.1–1.4T	$1.5–2.1T	$1.9–2.5T

Pension/retirement and insurance losses represent these investors' share of the economy-wide losses shown above—they are subsets, not additional losses. Retirement portfolios hold approximately $27 trillion in equities and $12 trillion in fixed income; insurance companies hold approximately $5.4 trillion in bonds, $1.35 trillion in equities, and $900 billion in mortgage/RE investments. We model their losses modeled in detail, incorporating portfolio-specific asset allocation and credit composition.

Structural Solutions

The report evaluates whether redistribution alone—specifically, a 3% tax on AI company revenues as proposed by Amodei—can close the projected consumption gap. Even under optimistic assumptions about AI industry revenue growth ($3 trillion), a 3% tax yields only $90 billion, covering at most 35% of the gap in the Light scenario and just 3% in the Aggressive scenario. For a 3% tax to fully close the gap at 10% displacement, AI revenues would need to reach approximately $36 trillion—more than the entire current US GDP.

The paper therefore argues for predistributive mechanisms—broad-based equity-linked compensation (BEC) and broadened corporate governance participation (BCGP)—that structure the economy for shared prosperity before displacement occurs, rather than relying solely on after-the-fact redistribution. These include employee and community ownership of AI infrastructure, equity-linked compensation for content creators and other contributors to AI value chains, and multistakeholder governance models that broaden participation in corporate decision-making, which can address AI safety and cognitive bias risks. The report also identifies an alignment of interest: AI companies themselves face material revenue contraction under displacement scenarios (the "AI revenue reflexivity problem"), making broad-based ownership not just sound social policy but a precondition for AI companies achieving the revenue scale their investors are pricing in.

Important Caveats and Modeling Limitations

This report is a **demand-side stress test**, not a comprehensive forecast of AI's net economic impact. The modeling framework is designed to quantify the financial transmission risks that arise from concentrated labor displacement and employment degradation—a feature acknowledged across both optimistic and pessimistic AI forecasts. Several important limitations should be borne in mind when interpreting the results.

The model does not incorporate AI-driven productivity gains or cost savings. To the extent that AI adoption reduces corporate operating costs, improves margins, or generates new categories of economic activity, the earnings declines, equity losses, and corporate default rates modeled in the report would be attenuated. The estimates should therefore be understood as modeling the demand-side risk in the absence of a fully offsetting supply-side response—a stress test of what happens if the productivity benefits are slower, more concentrated, or more uneven than optimists project. Three reasons motivate this choice: (1) productivity gains are distributed unevenly across firms and sectors, and the firms most exposed to demand contraction may not be those best positioned to realize AI cost savings; (2) there is a timing mismatch, as consumption losses are immediate while productivity gains require investment, adoption, and organizational restructuring that take quarters or years to materialize; and (3) the total cost of AI adoption—including compute infrastructure, integration, data preparation, and workforce retraining—remains uncertain, and may not fall as rapidly as projected.

The model does not incorporate policy intervention, monetary accommodation, or fiscal stimulus. In practice, the Federal Reserve would likely cut interest rates, and Congress would likely consider countercyclical fiscal measures. These responses could partially cushion the demand-side shock modeled here. However, the report notes that post-GFC policy tools have limits—particularly if the underlying cause of stress is structural displacement rather than a temporary liquidity shock—and that fiscal capacity may itself be constrained by the tax revenue erosion modeled. Furthermore given historical monetary and fiscal support response times, the cushioning effects would likely lag the displacement shock by quarters or years—precisely the window during which household debt defaults, consumption contraction, and portfolio impairments would be most acute. And the political capacity to deploy aggressive countercyclical fiscal support may itself be constrained: with US public debt already at elevated levels following successive rounds of crisis-era and pandemic-era stimulus, the political tolerance for additional deficit expansion—and the market's willingness to absorb it at favorable rates—cannot be assumed.

The model focuses on the United States (US) only. Global labor and consumer markets, international trade dynamics, and cross-border financial contagion are not modeled. For a more complete understanding of AI displacement risks, global integration would be required, and PDI intends to address this in future iterations.

Financial transmission channels are modeled sequentially but interact simultaneously. In reality, mortgage default waves simultaneously impair bank balance sheets, reduce household wealth, suppress consumer spending, and strain local government finances—each feeding back into the others. The report presents channels individually for analytical clarity, but the true value at risk under a disorderly displacement scenario is likely higher than what is modeled, and the channels are more deeply interconnected than the sequential presentation implies. Behavioral responses, international contagion, credit market freezes, and political instability are among the second- and third-order effects not captured.

The model does not take a position on the likelihood of any specific scenario. The paper does not predict that AI will cause 10%, 20% unemployment, or no unemployment at all. It models the financial consequences *if* displacement occurs at these levels—levels drawn from projections by Amodei and other credible sources—to enable scenario planning and stress testing. The Light scenario explicitly assumes no net job losses and demonstrates that even employment degradation alone generates meaningful systemic risk.

Default rates and market loss estimates are calibrated to GFC benchmarks, with adjustments for structural differences. The GFC was largely cyclical; AI displacement may be structural, with longer unemployment durations and permanent wage downgrades. The model presents ranges (low and high bounds) to reflect this uncertainty. The low bounds are typically anchored to GFC observed rates; the high bounds incorporate modest uplifts for potentially more severe displacement dynamics. These are not precise predictions but structured starting points for quantifying systemic risk.

The model uses a uniform average wage across displacement scenarios. The $67,920 mean annual wage is applied across all scenarios, recognizing that actual displacement will span both high-earning white-collar knowledge workers and lower-earning service and blue-collar workers. This simplifying assumption may overstate per-worker income loss in scenarios that disproportionately affect lower-wage workers, or understate it in scenarios concentrated among knowledge workers.

Taken together, these caveats mean the report’s estimates are best understood as a **structured analytical framework for evaluating demand-side systemic risk**—not as point forecasts of inevitable outcomes. The purpose is to catalyze informed scenario planning among business leaders, investors, policymakers, and the public, and to make the case that predistributive structural interventions merit serious consideration alongside traditional redistributive mechanisms.

Table of Contents

1. Considering AI Scenarios[1]

1.1 AI and Economic Growth

A growing body of economic research and industry analysis projects that AI will be net positive for economic growth. Goldman Sachs' *The Potentially Large Effects of Artificial Intelligence on Economic Growth* frames AI as a general-purpose technology that will reshape labor markets primarily through task-level automation rather than wholesale job elimination.[2] The report estimates that roughly two-thirds of current occupations are exposed to some degree of AI automation, with generative AI capable of substituting up to one-fourth of existing work tasks. However, they emphasize that this reflects potential exposure rather than direct displacement, since most jobs are only partially automatable. On the growth side, Goldman Sachs estimates that generative AI could raise annual US labor productivity growth by nearly 1.5 percentage points over a ten-year adoption period, with global GDP potentially increasing by approximately 7 percent over time.

These projections find broad expert support. Karger et al. (2026) surveyed academic economists, AI industry professionals, policy researchers, and superforecasters on AI's likely economic effects.[3] The median economist expects annual GDP growth of 2.5 %—above both the Congressional Budget Office's (CBO's) medium-run baseline of 2.0% and its long-run baseline of 1.7%. Even conditional on a "rapid" AI progress scenario in which AI systems surpass human performance on most cognitive and physical tasks by 2030, economists forecast GDP growth of approximately 3.5%.

Crucially, however, economists in this same rapid scenario also forecast the labor force participation rate falling from 62 to 55% by 2050, with roughly half that decline—equivalent to approximately 10 million lost jobs—attributable directly to AI, and the share of wealth held by the top 10% of households rising to 80%. In other words, the expert consensus itself contains a scenario in which GDP grows while employment contracts and inequality deepens substantially. Anthropic CEO Dario Amodei projects that AI could drive GDP growth of 5–20% annually while simultaneously causing unemployment of 10–20%, a combination he describes as a period of extreme economic volatility. He has also warned that AI could displace 50% of entry-level white-collar jobs within one to five years.[4]

[1] Note this report focuses primarily on the U.S. labor market. For a more accurate understanding of demand scenarios, global labor and consumer markets need to be considered. PDI seeks to integrate such considerations in future iterations of analysis.

[2] Joseph Briggs and Devesh Kodnani, "The Potentially Large Effects of Artificial Intelligence on Economic Growth," Goldman Sachs Global Investment Research, March 26, 2023, https://www.goldmansachs.com/insights/articles/generative-ai-could-raise-global-gdp-by-7-percent.

[3] Ezra Karger, Otto Kuusela, et al., "Forecasting the Economic Effects of AI," Forecasting Research Institute, March 2026, https://www.nber.org/papers/w35046. The survey was conducted October 2025–February 2026.

[4] Wall Street Journal, "Anthropic CEO Says Government Should Help Ensure AI's Economic Upside Is Shared," 2025, https://www.wsj.com/tech/ai/anthropic-ceo-says-government-should-help-ensure-ais-economic-upside-is-shared-1eab376c; Dario Amodei,

In considering scenarios, the Jevons paradox is also increasingly referenced. The paradox reflects the observation that when steam engines made coal more efficient in 1865, Britain did not burn less coal but more.[5] Apollo's Torsten Slok applies this logic directly to AI: when AI lowers the cost of professional services—legal, consulting, financial—the addressable market for those services expands and total employment grows.[6] Erik Brynjolfsson, one of the foremost economists of technology and productivity, has argued that AI efficiency gains can expand rather than contract economic activity, noting that coders, translators, and radiologists are already seeing growing employment alongside rising AI-driven productivity.[7] Microsoft CEO Satya Nadella has explicitly invoked the Jevons paradox to explain why his company is hiring more engineers, not fewer, as AI capabilities advance.[8] Slok points to falling youth unemployment and historically high levels of new business formation as early evidence that cheaper inputs are expanding markets.

One granular analysis of these dynamics comes from a BCG Henderson Institute microeconomic model, which moves beyond aggregate forecasts to assess AI's impact role by role across approximately 1,500 US occupations.[9] BCG estimates that over the next two to three years, 50 to 55% of US jobs will be reshaped by AI—meaning workers retain their roles but face substantially changed expectations for how they work and what they produce. Only 10 to 15% of jobs are estimated to be vulnerable to outright elimination over a four-to-five-year horizon. Building on Eloundou et al.'s (2024) task-level classification of AI automation potential,[10] Penn Wharton estimates that roughly two-fifths of jobs currently in the labor market fall into the exposed category, meaning generative AI could potentially automate at least half of its associated tasks.[11] The BCG report distinguishes between roles where AI substitutes for human labor and those where it augments it, and further differentiates by whether AI-driven productivity gains expand demand for the output (as in software engineering, where lower development costs may generate more projects) or leave demand bounded (as in call centers, where inbound volume is fixed by customer base

---

"The Adolescence of Technology," January 2026, https://www.darioamodei.com/essay/the-adolescence-of-technology; Axios, "Anthropic Raises $30 Billion at $380 Billion Valuation," May 28, 2025, https://www.axios.com/2025/05/28/ai-jobs-white-collar-unemployment-anthropic. He also raises a number of AI safety risks, including autonomy, misuse for destruction or power, and other societal impacts.

[5] William Stanley Jevons, *The Coal Question: An Inquiry Concerning the Progress of the Nation, and the Probable Exhaustion of Our Coal-Mines* (London: Macmillan, 1865).

[6] Torsten Slok, "The Jevons Employment Effect From AI," *The Daily Spark*, April 28, 2026, https://www.apollo.com/wealth/the-daily-spark/the-jevons-employment-effect-from-ai

[7] Erik Brynjolfsson, interview with NPR Planet Money, February 4, 2025, https://www.npr.org/sections/planet-money/2025/02/04/g-s1-46018/ai-deepseek-economics-jevons-paradox. See also Erik Brynjolfsson, Daniel Rock, and Chad Syverson, "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies," *American Economic Journal: Macroeconomics* 13, no. 1 (January 2021): 333–372, https://doi.org/10.1257/mac.20180386.

[8] Satya Nadella, cited in "Jevons Paradox: The 160-Year-Old Idea That Explains Why AI Is Creating More Jobs, Not Fewer," *Wholesale Investor*, March 26, 2026, https://www.wholesaleinvestor.com/jevons-paradox-the-160-year-old-idea-that-explains-why-ai-is-creating-more-jobs-not-fewer/.

[9] Greg Emerson, Matthew Kropp, et al., "AI Will Reshape More Jobs Than It Replaces," BCG Henderson Institute, April 3, 2026, https://www.bcg.com/publications/2026/ai-will-reshape-more-jobs-than-it-replaces.

[10] Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock, "GPTs Are GPTs: Labor Market Impact Potential of LLMs," Science 384, no. 6702 (June 21, 2024): 1306–1308, https://doi.org/10.1126/science.adj0998.

[11] 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/.

size). In the most favorable cases, with “amplified” and “rebalanced” roles, AI raises productivity while employment remains stable or grows.

Critically, however, even BCG’s analysis reveals a potential structural vulnerability at the heart of the optimistic case. In what the report terms “divergent” roles—approximately 12% of current jobs—AI and automation substitute for human tasks but expanding demand preserves employment at senior levels while eliminating entry-level and junior positions. The structured tasks traditionally performed by early-career workers are among the first to be automated, while the roles that persist require contextual judgment and coordination skills typically built through on-the-job experience, creating what BCG calls a “structural tension.” This finding aligns with Brynjolfsson, Chandar, and Chen (2025), who document a 16% relative employment decline for early-career workers in AI-exposed occupations since the widespread rollout of generative AI.[12] BCG also acknowledges that “substituted” roles—another 12% of jobs—face net elimination, with downward wage pressure on the positions that remain. BCG is explicit that its model is a microeconomic assessment and does not account for macroeconomic feedback effects, including precisely the aggregate demand dynamics and financial transmission channels that are the focus of this paper.

This discussion paper does not take a position on whether AI will be net GDP-positive over the long run and will ultimately prove beneficial. Rather, it models the financial transmission channels through which concentrated labor displacement—a feature acknowledged across both optimistic and pessimistic forecasts—could generate systemic credit stress, even in scenarios where aggregate output continues to grow, and even temporarily in a rapid transition. Three considerations motivate the stress-testing approach taken here.

Why Stress Testing Remains Necessary

First, the aggregate demand channel is direct and immediate. Consumer spending accounts for approximately 68–70% of US GDP**.**[13] Workers displaced by AI are disproportionately concentrated in middle-income, consumption-intensive cohorts with high marginal propensities to consume (MPCs).[14] The primary beneficiaries of AI-driven productivity gains—capital owners, high-skill complementary workers, and AI-adopting firms—have systematically lower MPCs. This means that even if aggregate income is preserved through productivity gains, the compositional shift from high-MPC displaced workers to low-MPC AI beneficiaries produces a net drag on consumer demand. The consumption loss is mechanical and immediate as displaced workers carry existing mortgage, consumer credit, and other debt obligations on

[12] Erik Brynjolfsson, Danielle Li Chandar, and Lindsey R. Chen, “Canaries in the Coal Mine? Early-Career Employment and AI Exposure,” Working Paper, 2025. https://digitaleconomy.stanford.edu/app/uploads/2025/11/CanariesintheCoalMine_Nov25.pdf

[13] U.S. Bureau of Economic Analysis, Shares of Gross Domestic Product: Personal Consumption Expenditures (DPCERE1Q156NBEA), Federal Reserve Bank of St. Louis (FRED), Q4 2025, https://fred.stlouisfed.org/series/DPCERE1Q156NBEA.

[14] The MPC is the proportion of additional income that a household spends on goods and services rather than savings.

fixed timelines. The offsetting forces (new job creation, fiscal transfers, investment-led demand) are uncertain and contingent on policy choices that may or may not materialize in time.

Second, the Jevons paradox has structural limitations in labor markets. The historical Jevons effect operated on a commodity input (coal) with effectively unlimited demand elasticity. Professional labor markets are different: the expansion of addressable demand for legal or consulting services, even if real, takes time to materialize and requires displaced workers to acquire new skills, find new clients, or start new firms. During the transition period—which could last years—displaced workers still carry existing debt obligations. The question for financial stability is not limited to whether the labor market eventually rebalances, but also what happens in the credit channels during the gap. As Brynjolfsson himself acknowledges, even in the optimistic scenario not all occupations will see the Jevons effect: if a machine can completely automate every task of a job, or if employers do not share productivity gains with workers, the result can be falling wages and displacement rather than expansion.[15] Moreover, the Jevons effect applies most naturally to tasks that become cheaper; it does not guarantee that the workers previously performing those tasks are the ones who benefit from the expanded market. Capital owners may benefit while workers do not. New entrants, AI-augmented competitors, and firms in lower-cost jurisdictions may capture the growth, while incumbent displaced firms and workers bear the adjustment costs.

Third, AI may accelerate pre-existing trends that have already been unfavorable to workers. The labor share has been declining in the US since the 1960s, though three-quarters of the entire post-1947 decline has occurred since the early 2000s. Labor's share of US output in the nonfarm business sector fell to 54.1% in Q1 2026—its lowest level since the BLS began recording the data in 1947, when it stood at 65.8%.[16] On a broader national-accounts basis, labor compensation accounted for only about 51% of US gross domestic income in early 2026, reflecting the growing shares accruing to profits, depreciation, interest, rents, and other forms of non-labor income.[17] Over the same period, corporate profits' share of gross domestic income rose from 7% in 1980 to 12.1%.[18]

The structural nature of this shift is illustrated by an IBM-to-Nvidia comparison: Nvidia is roughly twenty times as valuable and five times as profitable as IBM was in 1985 in inflation-adjusted terms, yet employs approximately a tenth as many people. Meanwhile, wage growth for non-supervisory workers has persistently lagged productivity growth. The Economic Policy Institute's productivity-pay analysis

[15] Brynjolfsson, NPR Planet Money interview, February 4, 2025: "If your employer doesn't share the fruits of higher productivity with you or if the machine makes your job easier to do and more people can do it, you might not see higher wages. You could see falling wages over time."

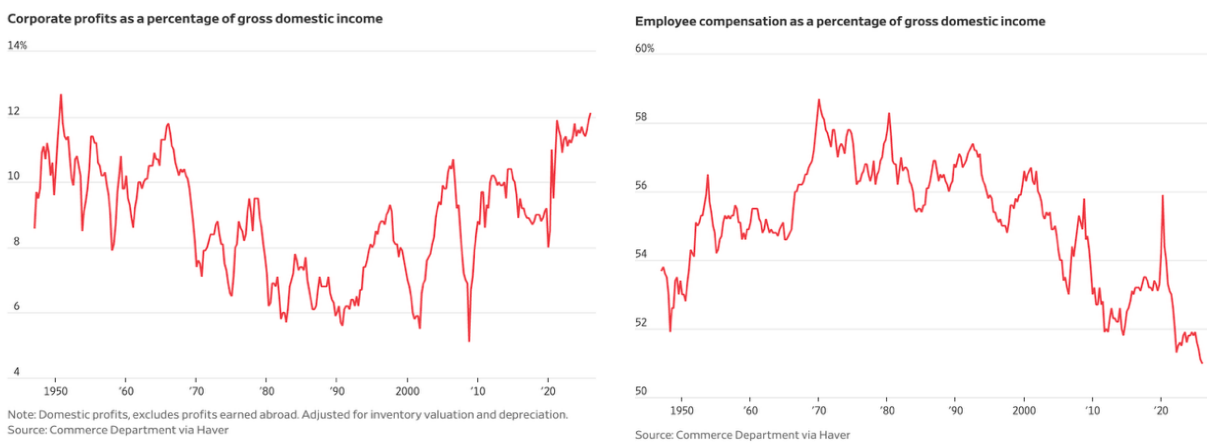
[16] U.S. Bureau of Labor Statistics, "Productivity and Costs, First Quarter 2026, Preliminary," news release USDL-26-0835, May 7, 2026, https://www.bls.gov/news.release/archives/prod2_05072026.htm; Fortune, "U.S. Workers Just Took Home Their Smallest Share of Capital Since 1947," January 2026, https://fortune.com/2026/01/13/us-workers-smallest-labor-share-gdp-on-record/; U.S. Bureau of Labor Statistics. "Labor share of output has declined since 1947." *The Economics Daily*, March 7, 2017. https://www.bls.gov/opub/ted/2017/labor-share-of-output-has-declined-since-1947.htm

[17] Greg Ip, "The Record Divide Between Corporate Profits and Worker Pay," *Wall Street Journal*, May 29, 2026, https://www.wsj.com/finance/stocks/the-record-divide-between-corporate-profits-and-worker-pay-ea4c75bc.

[18] Id.

documents that the gains from productivity growth have flowed disproportionately to highly compensated executives and to shareholders—the two key drivers of rising economic inequality since the late 1970s.[19] This is largely due to the structure of executive compensation being equity-linked and how financial capital has been valued disproportionately more relative to human capital (labor) and social capital (i.e. communities hosting infrastructure projects or content creators contributing to AI) inputs into the productivity process. In addition, corporate governance has increasingly prioritized shareholder returns over workforce investment.[20]

Figure 1: Employee Compensation and Corporate Profits as Shares of Gross Domestic Income, 1947-2025



Source: Commerce Department via Haver, as reported by Greg Ip, "The Record Divide Between Corporate Profits and Worker Pay," Wall Street Journal, May 28, 2026, https://www.wsj.com/finance/stocks/the-record-divide-between-corporate-profits-and-worker-pay-ea4c75bc.

Even when the economy has technically achieved full employment in recent years, the quality of that employment has changed substantially. The rise of gig work, independent contracting, and part-time positions without benefits means that "full employment" no longer implies stable, full-time, benefits-bearing jobs at living wages as it did in the postwar era.[21] The share of workers in alternative work arrangements is estimated to have grown from 10.7% in 2005 to as high as 15.8% by 2015, reflecting in part the expansion of platform-mediated work and firm strategies to reduce labor costs through contracting and reclassification.[22] A more recent study, building on the anonymous and aggregated ADP

---

[19] Economic Policy Institute, "The Productivity–Pay Gap," 2025, https://www.epi.org/productivity-pay-gap/. Net productivity grew 92.4% from 1979 to 2025 while a typical worker's compensation (hourly pay) grew by just 33.6%. If median hourly compensation had grown at the same rate as productivity over that period, the median worker would be making $9.00 more per hour.

[20] William Lazonick, "Profits Without Prosperity," *Harvard Business Review*, September 2014, https://hbr.org/2014/09/profits-without-prosperity. Lazonick documents the shift from "retain-and-reinvest" — in which corporations retained earnings and reinvested in workforce capabilities — to "downsize-and-distribute," in which corporations lay off experienced workers and distribute cash to shareholders via stock buybacks. See also William Lazonick and Mary O'Sullivan, "Maximizing Shareholder Value: A New Ideology for Corporate Governance," *Economy and Society* 29, no. 1 (2000): 13–35, https://doi.org/10.1080/030851400360541.

[21] Jacob S. Hacker, *The Great Risk Shift: The New Economic Insecurity and the Decline of the American Dream*, rev. and exp. ed. (New York: Oxford University Press, 2019). Hacker's central claim is that the U.S. economy has undergone a systematic shift of economic risk from employers, government, and collective institutions onto individual households. Importantly, he is not just talking about wages or jobs in isolation, but about the structure of employment, social insurance, and income security taken together.

[22] Lawrence F. Katz and Alan B. Krueger, "The Rise and Nature of Alternative Work Arrangements in the United States, 1995–2015," *ILR Review* 72, no. 2 (2019): 382–416, https://journals.sagepub.com/doi/10.1177/0019793918820008, using the RAND-Princeton Contingent Work Survey. According to the Bureau of Labor Statistics, the share of U.S. workers in alternative work arrangements was about 10% in 2005 and remained near 10% in 2017; see U.S. Bureau of Labor Statistics, Contingent and Alternative Employment Arrangements, February 2005,

payroll data of more than 1.1 million employers, found that individuals who received a short-term W-2 or a 1099 accounted for 27% of all jobs held in 2024.[23] The "fissuring of the workplace," as documented by former Department of Labor chief economist David Weil, describes how firms increasingly outsource functions that were once performed by employees, severing the employment relationship while maintaining the productive activity and widening profit margins for capital owners.[24] Meanwhile, benefits such as healthcare, defined benefit retirement accounts, and other protections have deteriorated, and more Americans are working multiple jobs to make ends meet.[25] Wealth concentration has increased steadily, with the top 10% of households now holding over 71% of total wealth.[26]

These are not speculative projections—they are the baseline conditions into which AI is being deployed. Acemoglu and Restrepo (2022) have found that between 50% and 70% of changes in the US wage structure over the last four decades are accounted for by relative wage declines of worker groups specialized in routine tasks in industries experiencing rapid automation.[27] They predict that as firms integrate AI, a shrinking share of revenue will go toward labor—replicating at the white-collar level what happened to blue-collar workers as manufacturing automated. Further, the declining labor share is not primarily a story of individual firms underpaying their workers. It reflects instead a compositional shift in which the fastest-growing companies—today's superstar technology firms—pay well but employ relatively few people. Alphabet's revenue grew 43% between 2022 and 2025 while headcount remained flat. The gains accrue to a narrow class of shareholders and highly compensated technical employees whose compensation is itself equity-linked, compounding wealth concentration at the top.[28]

---

https://www.bls.gov/news.release/archives/conemp_07272005.pdf; U.S. Bureau of Labor Statistics, Contingent and Alternative Employment Arrangements, May 2017, https://www.bls.gov/news.release/archives/conemp_06072018.pdf
Katz and Krueger attribute part of the divergence to Current Population Survey methodology undercounting certain forms of independent contracting, a view supported by IRS administrative data showing rising 1099 receipt and Schedule C filing rates over the same period. See Lawrence F. Katz and Alan B. Krueger, "Understanding Trends in Alternative Work Arrangements in the United States," *RSF: The Russell Sage Foundation Journal of the Social Sciences* 5, no. 5 (2019): 132–146. https://www.nber.org/system/files/working_papers/w25425/w25425.pdf
See also Emory Jackson, Adam Looney, and Shanthi Ramnath, "The Rise of Alternative Work Arrangements: Evidence and Implications for Tax Filing and Benefit Coverage," Office of Tax Analysis Working Paper 114, U.S. Department of the Treasury, 2017. https://home.treasury.gov/system/files/131/WP-114.pdf

[23] Łukasz Below, "The Gig Economy: A Tale of Two Labor Markets," ADP Research Institute, November 20, 2025, https://www.adpresearch.com/the-gig-economy-a-tale-of-two-labor-markets/. Only 1 in 10 workers were part of the gig economy in a typical month, but 1 in 4 had engaged in some sort of gig work during the previous 12 months.

[24] David Weil, *The Fissured Workplace: Why Work Became So Bad for So Many and What Can Be Done to Improve It* (Cambridge, MA: Harvard University Press, 2014), https://www.hup.harvard.edu/books/9780674975446

[25] CNBC, "More Americans with College Degrees Are Working Multiple Jobs," March 16, 2025, https://www.cnbc.com/2025/03/16/more-americans-with-college-degrees-are-working-multiple-jobs.html

[26] Federal Reserve Board of Governors, Distributional Financial Accounts of the United States, Table: "Distribution of Household Wealth," updated March 27, 2026; see also Federal Reserve Bank of St. Louis, "The State of U.S. Household Wealth," June 23, 2025, https://www.federalreserve.gov/releases/z1/dataviz/dfa/distribute/chart/; https://www.stlouisfed.org/open-vault/2025/june/the-state-of-us-household-wealth

[27] Daron Acemoglu and Pascual Restrepo, "Tasks, Automation, and the Rise in U.S. Wage Inequality," *Econometrica* 90, no. 5 (September 2022): 1973–2016, https://economics.mit.edu/sites/default/files/2022-10/Tasks%20Automation%20and%20the%20Rise%20in%20US%20Wage%20Inequality.pdf

[28] David Autor, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen, "The Fall of the Labor Share and the Rise of Superstar Firms," *Quarterly Journal of Economics* 135, no. 2 (May 2020): 645–709, https://doi.org/10.1093/qje/qjaa004; Thomas Philippon, *The Great Reversal: How America Gave Up on Free Markets* (Cambridge, MA: Harvard University Press, 2019), https://www.hup.harvard.edu/books/9780674237544; Daron Acemoglu and Pascual Restrepo, "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives* 33, no. 2 (Spring 2019): 3–30, https://doi.org/10.1257/jep.33.2.3

Generative AI dramatically expands the frontier of what counts as 'routine.' Depending on the long-term costs of compute relative to labor, AI is likely to deepen these dynamics for three reasons: it decomposes integrated jobs into separable tasks that are easier to contract out and automate (McKinsey estimates 60% of occupations have at least 30% automatable activities);[29] it lowers the coordination costs that historically favored employment over contracting, shifting the Coasean boundary between firm and market;[30] and the precedent from rideshare platforms—which reclassified 1.5–2 million workers within five years in a single industry[31]—suggests AI's broader scope could produce much larger shifts across professional services, finance, media, and technology simultaneously.

PIMCO's February 2026 analysis highlights how income shifts structurally toward capital when firms rely increasingly on intangible capital—software, intellectual property, data, algorithms—that scales with little additional labor.[32] If AI amplifies the capital-labor substitution dynamics, superstar-firm concentration, and winner-take-most market structures that have driven these trends, the distributional consequences could be severe even in a context of rising aggregate output. Even Acemoglu (2024), who offers the most restrained estimates of AI's impact on growth, predicts that AI will widen the gap between capital and labor income.[33] Acemoglu frames this explicitly as "productivity without prosperity": aggregate output rises while labor's share of that output falls, concentrating gains at the top of the income and wealth distribution. The Karger et al. (2026) finding that economists forecast wealth inequality rising to 80% under the rapid AI scenario—from an already historically elevated 71%—confirms that this is not a fringe concern. And while technology may be expected to compensate for declining purchasing power by deflating the costs of goods and services, recent history has shown a pattern of rising inflation when it comes to costs of living, even as certain goods and services have become cheaper with technological efficiencies.

Implications for Financial Stability

PIMCO's February 2026 analysis warns that declining labor share is making the US economy structurally more volatile and more sensitive to asset price swings: as income shifts from wages to capital returns, aggregate consumption becomes increasingly dependent on equity valuations, credit conditions, and

---

[29] McKinsey Global Institute, A Future That Works: Automation, Employment, and Productivity, January 2017, https://www.mckinsey.com/~/media/mckinsey/featured%20insights/digital%20disruption/harnessing%20automation%20for%20a%20future%20that%20works/mgi-a-future-that-works_in-brief.pdf. See also McKinsey Global Institute, Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation, December 2017, https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages

[30] Ronald H. Coase, "The Nature of the Firm," *Economica* 4, no. 16 (November 1937): 386–405; David Weil, The Fissured Workplace: Why Work Became So Bad for So Many and What Can Be Done to Improve It (Cambridge, MA: Harvard University Press, 2014).

[31] As of 2024, Uber alone had approximately 1.5 million drivers in the U.S. classified as independent contractors, with Lyft adding several hundred thousand more; see "Employee or Independent Contractor? A Legal Analysis of Uber's Worker Misclassification," *Columbia Undergraduate Law Review*, September 2024, https://www.culawreview.org/current-events-2/employee-or-independent-contractor-a-legal-analysis-of-ubers-worker-misclassification.

[32] PIMCO, "Why U.S. Productivity Gains No Longer Reach Workers," February 2026, https://www.pimco.com/us/en/insights/why-us-productivity-gains-no-longer-reach-workers

[33] Daron Acemoglu, "The Simple Macroeconomics of AI," *Economic Policy* 40, no. 121 (January 2025): 13–58, https://doi.org/10.1093/epolic/eiae042

fiscal support rather than on earned income.[34] Further, since higher-income households who capture these capital gains have lower MPCs, that consumption is more fragile. PIMCO further notes that rising financial stability risks are a potential by-product of widespread AI adoption, observing that boom-and-bust investment cycles have historically coincided with the proliferation of new general-purpose technologies, and that elevated US equity valuations make the current cycle particularly exposed.

The relevant question for financial stability is not whether GDP nets positive in the long run, but whether the specific households and firms bearing debt exposure experience income disruption sufficient to impair debt service—and whether the transition path is volatile enough to disrupt financial markets. Rapid displacement concentrated in specific sectors and geographies can produce localized credit shocks—mortgage delinquencies in AI-exposed metro areas, consumer credit losses among displaced cohorts, corporate defaults among firms that depend on the spending power of displaced workers—that transmit through interconnected financial channels before any rebalancing occurs. Investment, as Leão and Leão (2024) confirm, is only economically rational when firms anticipate future demand; its capacity-building effects eventually exceed its demand-generating effects, so it cannot substitute for lost consumption indefinitely.[35] Pettis (2016) and the Bank for International Settlements (2017) reach similar conclusions about the limits of investment-led growth when consumption is weakening.[36] The scenarios modeled in this paper ask: what are the financial consequences if the optimistic forecasts are right about productivity but the transition is slower, more uneven, or more disruptive than assumed?

A scenario in which AI drives aggregate growth while simultaneously displacing a significant share of workers is not a counterargument to this analysis; it is precisely the condition under which the financial transmission channels modeled here become most dangerous, because household-level distress may persist without triggering the macroeconomic warning signals that typically prompt policy intervention. Pre-GFC GDP was growing while household balance sheets were quietly deteriorating—the aggregate masked the channel-level fragility until it was too late.

Like other market actors, PDI recognizes the need to seriously consider Amodei's unemployment projections, while also acknowledging they may not come to fruition. This discussion paper offers an opportunity to prepare for potential economic and, albeit more tangentially, safety risks by exploring structural solutions—broad-based equity-linked compensation (“BEC”) and broadening corporate governance participation (“BCGP” or multistakeholder governance) approaches—that are largely absent

[34] PIMCO, “Why U.S. Productivity Gains No Longer Reach Workers,” February 2026, https://www.pimco.com/us/en/insights/why-us-productivity-gains-no-longer-reach-workers

[35] Emanuel Leão and Pedro Leão, “The Paradox of Investment: Why Investment Generates Excess Capacity in the Long Run,” Review of Political Economy, 2024.

[36] Michael Pettis, “Excess Savings and Global Imbalances,” Carnegie Endowment for International Peace, 2016; Bank for International Settlements, 87th Annual Report, June 2017.

from the current conversation but could meaningfully address economic risks he and others such as James Van Geelen of Citrini Research identify.

1.2 Workforce Displacement and Employment Degradation Scenarios

This discussion paper models four labor displacement scenarios derived from unemployment projections by Amodei (2026) and others, ranging from 10% to 20% unemployment. But full displacement with outright job losses is only one channel of disruption. A parallel and often underappreciated risk is workforce degradation: workers reclassified from full-time employment into gig or contractor status, nominally still employed but on fundamentally different economic terms. This channel is invisible to headline labor market metrics—unemployment stays low, GDP may grow—yet produces material income losses, benefit elimination, higher income volatility, and cascading effects on retirement contributions, payroll taxes, and debt default risk.

Both channels are parameterized across all four scenarios below. Note that the share of the non-displaced workforce reclassified from employee to contractor status—the “gig shift rate” represents an *incremental* shift attributable to AI, beyond the existing baseline of alternative work arrangements. This rate is calibrated relative to pre-AI historical trends: 10% of the workforce in the Light scenario implies roughly a 3–4x acceleration of the historical pace over 5 years.[37] In the Moderate, High, and Aggressive scenarios, the gig transition rate progressively declines as AI increasingly replaces roles entirely rather than downgrading them to precarious work.[38]

[37] As discussed, the empirical basis for gig transition rates is contested. The Bureau of Labor Statistics' Contingent Worker Supplement found the share of workers covered by alternative employment arrangements roughly flat at approximately 10% in both 2005 and 2017. Katz and Krueger's RAND-Princeton Contingent Work Survey documented a rise from approximately 10.1% to 15.8% of workers in alternative arrangements between 2005 and 2015 — a 5.7 percentage point increase over ten years, or roughly 0.57 percentage points per year. See footnote 25. Katz and Krueger attribute part of this divergence to methodological undercounting of certain forms of independent contracting. This model adopts Katz and Krueger's higher estimate as the more plausible pre-AI baseline, given that their finding is corroborated by independent IRS administrative data. Our scenarios are not extrapolations of this historical trend — they are forward-looking estimates of how AI could dramatically accelerate the shift toward precarious work as firms use automation to reclassify, outsource, or restructure roles that were previously full-time positions.

[38] The two channels are partially substitutive: in milder scenarios, AI reshapes work without eliminating it, producing widespread reclassification with modest displacement; in harsher scenarios, disruption manifests primarily as outright job loss, leaving less room for degraded-but-retained employment.

Table 4: Workforce Displacement and Employment Degradation Scenarios

Scenario	Unemployment Rate	Gig Shift Rate	Description
Light	4.4%	10%	The economy continues to operate with its current unemployment rate (~4.4%). AI does not produce net job losses beyond the existing baseline, but the terms of employment deteriorate as 10% of workers are reclassified from salaried positions to gig and contract arrangements.
Moderate	10%	7%	Dario Amodei's lower-bound estimate. AI fully displaces 5.6% of workers beyond the existing unemployment baseline rate (~4.4%), bringing total unemployment to 10%. An additional 7% of workers are reclassified from salaried positions to gig and contract arrangements.
High	15%	5%	Dario Amodei's mid-range estimate. AI fully displaces 10.6% of workers beyond the existing unemployment baseline rate (~4.4%), bringing total unemployment to 15%. An additional 5% of workers are reclassified from salaried positions to gig and contract arrangements.
Aggressive	20%	3%	Dario Amodei's upper-range estimate. AI fully displaces 15.6% of workers beyond the existing unemployment baseline rate (~4.4%), bringing total unemployment to 20%. An additional 3% of workers are reclassified from salaried positions to gig and contract arrangements.

The US currently employs approximately 158.4 million nonfarm workers, with a mean annual wage of $67,920, total compensation of approximately $13.1 trillion annually, and a current unemployment rate of 4.4%.[39] The displacement calculations in this report use the $67,920 mean wage figure across scenarios, since it represents the income workers directly lose when unemployed, recognizing that displacement will span both white-collar knowledge workers (who earn above this average) and blue-collar and service workers (who earn below it). It is worth noting that even at these levels there is significant debate about whether such income constitutes a living wage or can sustain durable GDP growth.[40]

Workers reclassified from full-time employment to contractor or gig status typically earn less for comparable work. Research suggests that earnings discounts depend on occupation and context. ADP Research Institute payroll data shows that temporary employees earn 35–44% less per hour than traditional W-2 workers, depending on whether the comparison uses median or average wages.[41] In

[39] U.S. Bureau of Labor Statistics, Current Employment Statistics, Nonfarm Payroll Employment, January 2026 (benchmark-revised), U.S. Department of Labor, https://www.bls.gov/news.release/empsit.nr0.htm; Bureau of Economic Analysis, National Income and Product Accounts, Compensation of Employees (SAAR), September 2025, accessed via Federal Reserve Economic Data (FRED), https://fred.stlouisfed.org/series/A576RC1; U.S. Bureau of Labor Statistics, Occupational Employment and Wage Statistics (OEWS), May 2024, https://data.bls.gov/oes/ (includes employer-paid benefits and social insurance contributions in addition to wages and salaries); U.S. Bureau of Labor Statistics, Unemployment Rate (Current Population Survey), February 2026, https://www.bls.gov/cps/

[40] See for example Michael W. Green, "Part 1: My Life Is a Lie," Yes I Give a Fig (Substack), 2025/2026, https://www.yesigiveafig.com/p/part-1-my-life-is-a-lie

[41] Łukasz Below, 'The Gig Economy: A Tale of Two Labor Markets,' ADP Research Institute, November 20, 2025, https://www.adpresearch.com/the-gig-economy-a-tale-of-two-labor-markets/. ADP's payroll data reports median hourly pay of $15 for temporary employees versus $23 for all U.S. workers (a 35% discount); average hourly pay of $19 for temp workers versus $34 for traditional

platform labor markets, the discounts can be steeper: JPMorgan Chase Institute research found that average transportation worker earnings declined approximately 53% between 2013 and 2017 as driver supply saturation compressed rates,[42] and the Economic Policy Institute estimated Uber driver net earnings at $9.21 per hour after expenses.[43] Importantly, not all gig workers earn less than their W-2 equivalents. Distributional analysis shows that gig work is not a uniform experience but a spectrum from lower-paid, less-secure roles to more high-skill independent contractors who command premium rates.[44] This said, workers involuntarily displaced into gig or contract status by AI are unlikely to enter the market with established client bases or specialized reputations, and are more likely to experience outcomes closer to that of a temporary worker in the spectrum.

To be conservative, our model applies gross wage haircuts that remain within the lower end of the observed range, scaling from 15% in the Light scenario to 30% in the Aggressive scenario. The Light scenario assumes the most employable workers transition first, retaining some degree of bargaining power and adjacent-skill transferability. As displacement broadens into mid-skill occupations and labor market saturation grows, the Moderate and High scenarios apply progressively steeper haircuts. Note that these haircut percentages do not account for the additional loss of employer-provided benefits.[45] All four scenarios remain within the established range of contractor and freelancer earnings gaps and well below the 35–44% discount observed for temporary workers and the 53% platform-market extreme.

Table 5: AI Displacement and Gig Transition: Income Loss by Scenario

	Light	Moderate	High	Aggressive
Workers Fully Displaced (incremental beyond 4.4% baseline)	0.0M	8.9M	16.8M	24.7M
Annual Income Lost from Displacement	$0B	$602.5B	$1.1T	$1.7T
Workers Shifted to Gig	15.8M	10.5M	7.1M	4.0M
Annual Income Lost from Gig Transition	$161.4B (15% haircut)	$142.2B (20% haircut)	$120.2B (25% haircut)	$81.7B (30% haircut)
Total Workers at Risk	15.8M	19.3M	23.9M	28.7M
Total Annual Income Lost	$161.4B	$744.7B	$1.3T	$1.8T

W-2 employees (a 44% discount). Independent contractors, by contrast, earn a median of $25/hr and an average of ~$39/hr, reflecting the high-skill, voluntary end of the gig spectrum.

[42] Diana Farrell, Fiona Greig, and Amar Hamoudi, "The Online Platform Economy in 2018: Drivers, Workers, Sellers, and Lessors," JPMorgan Chase Institute, September 2019, https://www.jpmorganchase.com/institute/research/labor-markets/report-ope-2018.

[43] Lawrence Mishel, "Uber and the Labor Market," Economic Policy Institute, May 15, 2018, https://www.epi.org/publication/uber-and-the-labor-market-uber-drivers-compensation-wages-and-the-scale-of-uber-and-the-gig-economy/.

[44] ADP payroll data shows nearly 7% of independent contractors earn more than $100 per hour, compared with 4.5% of traditional W-2 employees. These top earners—consultants, legal professionals, software developers, and technical experts—command premium rates for specialized project-based work. Łukasz Below, 'The Gig Economy: A Tale of Two Labor Markets,' ADP Research Institute, November 20, 2025, https://www.adpresearch.com/the-gig-economy-a-tale-of-two-labor-markets/.

[45] When a worker shifts from employee to contractor status, all employer-paid supplements vanish: health insurance premiums, retirement plan contributions, and the employer's share of payroll taxes. Gig workers also face substantially higher income volatility than salaried employees, which elevates default risk on mortgages, credit cards, auto loans, and student loans — this effect is incorporated into the default rate assumptions, which are calibrated to reflect the full range of labor market deterioration in each scenario.

Workers shifted to gig employment is calculated from the non-displaced population: total nonfarm employment (158.4 million) minus displaced workers, multiplied by the gig shift rate.

1.3 The Consumption Channel

Consumer spending accounts for 68% of US GDP, or approximately $21.4 trillion.[46] Research on the MPC suggests that displaced workers reduce corresponding consumption by roughly $0.65–0.80 per dollar of income lost, with lower-income workers at the higher end and higher-income knowledge workers at the lower end.[47] Using a blended MPC of 0.70 for the mixed population of affected workers, we estimate consumption loss from both displacement and gig transition income loss combined. The gig transition adds a meaningful consumption channel that is absent from conventional displacement analysis. Gig-transitioned workers retain most of their income, so the per-worker consumption impact is smaller than that of displaced workers—but it is spread across a larger population.

Table 6 summarizes the resulting estimates of income loss, consumption contraction, and GDP impact. To contextualize these results, each scenario is benchmarked against a GFC-equivalent stress level, incorporating both displacement and gig-transition income loss. For reference, during the GFC, the unemployment rate peaked at 10.2% (October 2009),[48] approximately 6.9 million workers were displaced,[49] and total annual income loss was approximately $300 billion (in 2008 dollars).[50] The Credit Stress (× GFC) metric is a summary measure of total labor-market-driven borrower stress relative to the GFC benchmark.[51]

---

[46] U.S. Bureau of Economic Analysis, Shares of Gross Domestic Product: Personal Consumption Expenditures (DPCERE1Q156NBEA), Federal Reserve Bank of St. Louis (FRED), Q4 2025, https://fred.stlouisfed.org/series/DPCERE1Q156NBEA.

[47] David S. Johnson, Jonathan A. Parker, and Nicholas S. Souleles, "Household Expenditure and the Income Tax Rebates of 2001," *American Economic Review* 96, no. 5 (December 2006): 1589–1610, https://doi.org/10.1257/aer.96.5.1589; Tullio Jappelli and Luigi Pistaferri, "Fiscal Policy and MPC Heterogeneity," *American Economic Journal: Macroeconomics* 6, no. 4 (October 2014): 107–136, https://doi.org/10.1257/mac.6.4.107.

[48] U.S. Bureau of Labor Statistics, "The Employment Situation—October 2009," USDL-09-1331, news release, November 6, 2009, https://www.bls.gov/news.release/archives/empsit_11062009.pdf.

[49] U.S. Bureau of Labor Statistics, "Worker Displacement: 2007–2009," USDL-10-1174, news release, August 26, 2010, https://www.bls.gov/news.release/archives/disp_08262010.htm. The 6.9 million figure reflects workers whose positions were eliminated during the 2007–2009 recession), not total unemployment — making it comparable to the incremental displacement modeled in our scenarios, which measures job losses above the 4.4% baseline unemployment rate.

[50] Our estimate calculated as 6.9 million displaced workers × $42,270 average annual wage = approximately $292 billion (rounded to ~$300 billion). The average annual wage figure is from U.S. Bureau of Labor Statistics, 'Occupational Employment and Wages, May 2008,' USDL-09-0478, May 1, 2009, https://www.bls.gov/news.release/archives/ocwage_05012009.pdf. This is an approximate figure intended to provide a rough order-of-magnitude comparison with the scenario income losses modeled in this paper; actual GFC income losses varied by occupation, duration of unemployment, and degree of wage reduction upon re-employment.

[51] It is constructed by combining the incremental unemployment rate (above the 4.4% baseline) with the gig-transition stress — calculated as the gig shift rate multiplied by the wage haircut and a fragility parameter (λ) that reflects the elevated default risk associated with volatile gig income — into a single blended stress rate, then dividing by the equivalent GFC stress rate. A value of 1.0 corresponds to GFC-equivalent stress; values above 1.0 indicate greater total labor-market disruption. The Moderate scenario (1.31×) exceeds the GFC despite matching its unemployment rate because the metric captures the additional stress from gig-related income loss, which was not a significant feature of the GFC crisis. This metric serves as a common scaling variable for calibrating default rates and credit outcomes throughout the model. The full construction methodology, including variable definitions and the fragility parameter, is detailed in Appendix B.1.

Table 6: Summary of income loss, consumption contraction, and GDP impact.

	GFC	Light	Moderate	High	Aggressive
Unemployment rate	~10.2%	4.4%	10.0%	15.0%	20.0%
Total annual income lost	~$300B	$160B	$740B	$1.3T	$1.8T
Total consumption loss (% GDP)	~3.5%	0.9%	4.0%	6.7%	9.3%
Estimated GDP contraction (%)	~4.3%	1.0%	4.9%	8.2%	11.5%
Credit Stress (× GFC)	1	0.33	1.31	2.17	2.99

Even with zero net job losses, the shift of approximately 16 million workers into precarious employment reduces aggregate wage income by roughly $160 billion, producing a GDP contraction of approximately 1.0%. This illustrates that a shift towards lower quality employment can generate meaningful macroeconomic drag well before it registers in headline unemployment figures.

The Moderate scenario (4.9% GDP contraction) slightly exceeds the GFC experience despite matching its unemployment rate, because the model captures an additional channel absent from conventional recession analysis: the partial income loss of millions of workers shifted into lower-paid gig employment, which amplifies the consumption shock beyond what unemployment alone would produce. As scenarios intensify, the composition of stress shifts: the more severe scenarios are characterized not only by greater overall disruption, but by a growing share of that stress coming from full displacement rather than partial income loss—a transition that increases borrower-level severity and amplifies macroeconomic impacts. The High (8.2%) and Aggressive (11.5%) scenarios substantially exceed the GFC and would represent unprecedented postwar contractions.

Taken together, these results underscore that the economic consequences of AI depend not only on how many jobs are lost, but on how income is distributed across the workforce and how that distribution evolves under different disruption pathways. The consumption contraction modeled here is the first-order shock that propagates through the credit, equity, retirement, insurance, and fiscal channels analyzed in Section 2. Moreover, our model traces GDP impact primarily through the consumption channel: displacement reduces household income, which reduces spending, which contracts aggregate demand. We do not model potential offsetting contributions—AI-driven productivity gains accruing to firms and capital owners, increased corporate investment, fiscal stimulus, or monetary policy accommodation—that could partially sustain aggregate output even as household-level distress deepens. To the extent that these forces materialize, the GDP contraction modeled here would be smaller than projected. However, even under optimistic assumptions, the distributional structure of AI's gains means that aggregate demand would still face downward pressure. The compositional shift from high-MPC displaced workers to low-MPC AI beneficiaries still produces a drag on consumer demand. This means that even in a scenario where aggregate GDP is sustained by productivity gains and investment, the specific households and firms bearing debt exposure could still experience the income disruption modeled below. The relevant question for financial stability is not whether GDP nets positive, but whether the transition path generates sufficient credit stress to trigger cascading losses across interconnected channels.

1.4 AI Industry Revenue and the Limits of a 3% Tax

Estimates of the global AI market (depending on definition of the market) in 2025 range from $255 billion (core AI software)[52] to $758 billion[53] (broader definitions including hardware, services, and enterprise applications), with most major research firms clustering around $300–400 billion—
Grand View Research at $391 billion[54], MarketsandMarkets at $372 billion[55], and Fortune Business Insights at $294 billion[56]. US companies account for 35–40% of global revenue. Conservative projections place US AI company revenue at $400–500 billion by 2033[57], optimistic estimates reach $700–800 billion[58]. Amodei has projected that the AI industry could see trillions in annual compute spending as soon as 2028–2029, with Anthropic itself potentially reaching $1 trillion in revenue if current growth trajectories hold[59].

These projections take on new significance considering Anthropic's own trajectory. The company recently closed a $30 billion Series G round at a $380 billion post-money valuation, with annualized revenue of $14 billion at the time—itself representing more than tenfold growth over three years[60]. That figure has since accelerated dramatically: by April 2026, Anthropic's annualized revenue run rate had surpassed $30 billion, up from $9 billion at the end of 2025, with more than 1,000 enterprise customers spending over $1 million annually—a figure that doubled in under two months[61]. Investors have since approached the company with offers valuing it at approximately $800 billion, more than doubling its February valuation[62]. If a single AI company can reach this scale this quickly, the higher-end aggregate industry figures may prove more realistic than the conservative ones.

---

[52] Statista. *Artificial Intelligence — Worldwide Market Forecast*. https://www.statista.com/topics/3104/artificial-intelligence-ai-worldwide/
[53] Precedence Research. *Artificial Intelligence Market Size, 2025–2035*. https://www.precedenceresearch.com/artificial-intelligence-market
[54] Grand View Research. *Artificial Intelligence Market Size & Trends Report, 2033*. https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market
[55] MarketsandMarkets. *Artificial Intelligence Market Report, 2025–2032*. https://www.marketsandmarkets.com/Market-Reports/artificial-intelligence-market-74851580.html
[56] Fortune Business Insights. *Artificial Intelligence Market Size & Growth, 2034*. https://www.fortunebusinessinsights.com/industry-reports/artificial-intelligence-market-100114
[57] Grand View Research. *Artificial Intelligence Market Size & Trends Report, 2033*. https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market
[58] MarketsandMarkets. *Artificial Intelligence Market Report, 2025–2032*. https://www.marketsandmarkets.com/Market-Reports/artificial-intelligence-market-74851580.html
[59] Fortune. "Anthropic CEO Dario Amodei explains his spending caution." February 14, 2026. https://fortune.com/2026/02/14/anthropic-ceo-dario-amodei-spending-capex-risk-ai-revenue-forecasts-bankruptcy/
[60] Leswing, K. "Anthropic closes $30 billion funding round as cash keeps flowing into top AI startups." *CNBC*, February 12, 2026. https://www.cnbc.com/2026/02/12/anthropic-closes-30-billion-funding-round-at-380-billion-valuation.html
[61] Bloomberg. "Anthropic Tops $30 Billion Run Rate, Seals Broadcom Deal." April 7, 2026. https://www.bloomberg.com/news/articles/2026-04-06/broadcom-confirms-deal-to-ship-google-tpu-chips-to-anthropic
[62] Bloomberg. "Anthropic Attracts Investor Offers at an $800 Billion Valuation." April 14, 2026. https://www.bloomberg.com/news/articles/2026-04-14/anthropic-attracts-investor-offers-at-a-800-billion-valuation

Amodei has proposed a 3% tax on AI company revenues for redistribution. The math illustrates why redistribution alone falls short in compensating for consumption resulting from declines in income. The below table illustrates the percent of the consumption gap such a tax-and-redistribute mechanism would cover:

Table 7: Estimated Coverage of the Consumption Gap Under a 3% AI Revenue Tax-and-Redistributive Mechanism

AI Annualized Revenue Assumption	3% Tax Yield	% of Gap (Light)	% of Gap (Moderate)	% of Gap (High)	% of Gap (Aggressive)
$500B (conservative)	$15B	5.86%	1.26%	0.75%	0.53%
$3T (Amodei projection)	$90B	35.15%	7.57%	4.47%	3.21%

For a 3% tax to fully cover the consumption shortfall at 10% displacement, AI revenues would need to reach ~$36 trillion—more than the entire current US GDP. Importantly, even these estimates may overstate the tax yield. As we detail, AI industry revenue is itself at risk under the collapse scenario: if mass displacement suppresses consumer spending, the enterprise customers, consumers, and advertisers who fund AI companies lose revenue too, potentially further reducing the tax base.

This is not a criticism of Amodei's proposal—every contribution helps. But it illustrates why predistributive mechanisms are structurally necessary to close the gap in the scenario he portrays—where: 1) BEC ownership stakes grow in value alongside AI-driven productivity, and 2) corporate governance is reformed to include workers, communities, and consumers. Redistribution can then address the remaining shortfall and support reskilling where necessary.

2. Financial Transmission Channels and Portfolio Impacts

The consumption contraction modeled in Section 1 is the first-order shock. This section traces how that shock propagates through interconnected financial systems—the mechanism that transforms a labor market disruption into a systemic financial risk comparable to or exceeding the GFC.

We model the transmission through three categories of channels. The first comprises direct credit and market impacts: mortgage and household debt defaults, corporate debt defaults, corporate bond mark-to-market losses, and equity market decline. These represent losses crystallizing in specific asset classes as income disruption impairs borrowers and weakens corporate earnings. The second category traces how those asset-level losses flow through to investor portfolios, with a focus on pensions and retirement assets and insurance industry exposure as illustrative. The third category addresses fiscal and structural feedback effects: Social Security acceleration, tax revenue erosion, and the AI revenue reflexivity trap. These are not portfolio losses in the traditional sense but systemic dynamics that amplify and entrench the crisis—shrinking the public safety net and the tax base at the precise moment both are most needed and undermining the AI companies whose revenues depend on the consumer spending being destroyed.

This model captures the demand-side transmission from displacement to consumption contraction to corporate earnings decline. **It does not model the offsetting supply-side effect:** AI adoption that reduces corporate costs, potentially improving margins and partially sustaining earnings even as revenues fall. In practice, both forces would operate simultaneously, and the net effect on corporate earnings depends on whether AI-driven cost savings outpace AI-driven revenue losses from weaker consumer demand. This limitation applies primarily to the corporate channels—corporate debt defaults, mark-to-market losses, and equity market decline, rather than household debt defaults driven by borrower-level income disruption, which AI-driven corporate productivity gains do not directly mitigate.

For the corporate channels, we do not attempt to model the productivity offset for three reasons. First, the gains are distributed unevenly: capital-light, AI-native firms may see significant margin improvement, while consumer-facing firms dependent on the spending of displaced workers could face revenue losses that no amount of cost reduction can fully offset. The firms most exposed to demand contraction may not be the firms best positioned to realize AI productivity gains. Second, there is a timing mismatch: consumption losses are immediate and mechanical (displaced workers stop spending on fixed timelines), while productivity gains require investment, adoption, and organizational restructuring that take quarters or years to materialize—a gap during which the credit stress modeled here would already be propagating through financial channels.

Third, the scale of AI-driven productivity gains depends on the total cost of AI adoption, which remains uncertain. Compute costs are a significant and growing expense: major technology firms are investing hundreds of billions annually in AI infrastructure, and it is not yet clear whether the productivity returns will justify these outlays across the broader corporate sector. If compute costs do not fall as rapidly as projected, or if the full cost of enterprise AI deployment—including infrastructure, integration, data preparation, workforce retraining, and ongoing operational expenses—proves substantially higher than the cost of the human labor it replaces, the anticipated productivity offset may not materialize, or may be confined to a narrow set of capital-rich firms that can absorb the upfront investment. Conversely, if compute costs fall rapidly and deployment proves straightforward, the offset could be larger than assumed. This uncertainty cuts both ways, and the model does not attempt to forecast it.

To the extent that AI-driven productivity gains materialize quickly and broadly, the earnings declines, equity losses, and corporate default rates modeled in this paper would be attenuated. The estimates should therefore be understood as modeling the demand-side risk in the absence of a fully offsetting supply-side response—a stress test of what happens if the productivity benefits are slower, more concentrated, or more uneven than optimists assume. In addition, the economy is a far more complex system. These channels do not operate in isolation—they interact with and amplify one another in ways that are difficult to model with precision. A mortgage default wave, for instance, simultaneously impairs bank balance sheets, reduces household wealth, suppresses consumer spending, and strains local government finances, each of which feeds back into the others. There are certainly additional feedback loops, other nonlinear dynamics, and second- and third-order effects—behavioral responses (including monetary policy), international contagion, credit market freezes, political instability—that our framework does not capture. The figures in this section should therefore be understood as a structured starting point for quantifying systemic risk, not a complete accounting of it. The true value at risk under a disorderly displacement scenario is likely higher than what we model here, and the channels we identify are more deeply interconnected than our sequential presentation implies.

2.1 Mortgage and Household Debt Contagion

Summary

Total US household debt reached $18.8 trillion as of Q4 2025. This section models the four largest categories—mortgages ($13.2 trillion), credit cards ($1.28 trillion), auto loans ($1.67 trillion), and student loans ($1.66 trillion)—which together account for approximately $17.8 trillion, 95% of the total. [63] Displaced workers carry fixed monthly obligations across all four categories that do not adjust when income disappears. The table below summarizes estimated defaults across the four scenarios; the sections that follow go into more detail on each asset class.

[63] Federal Reserve Bank of New York, “Quarterly Report on Household Debt and Credit, 2025:Q4,” Center for Microeconomic Data, released February 2026, https://www.newyorkfed.org/microeconomics/hhdc. The remaining ~$1 trillion, primarily home equity lines of credit, is not modeled separately.

Table 8: Estimated Household Debt Defaults by Scenario ($18.8T total outstanding)

Scenario	Mortgages	Credit Cards	Auto Loans	Student Loans	Total Household Debt Defaults
Light	$93.6–107.7B	$11.7–13.4B	$3.3–3.8B	$24.3–27.9B	$132.9–152.8B
Moderate	$288.5–292.5B	$35.9–36.4B	$10.3–10.4B	$64.8–75.8B	$399.5–415.2B
High	$387.0–463.5B	$48.2–57.7B	$13.8–16.5B	$109.4–120.1B	$558.4–657.9B
Aggressive	$486.4–678.1B	$60.6–84.5B	$17.3–24.1B	$166.9–175.8B	$731.2–962.5B

These estimates capture direct defaults by the at-risk population of displaced and gig-transitioned workers only. They do not account for indirect effects: credit tightening by lenders, asset depreciation as forced sales flood markets, or the economic anxiety that increases delinquency among non-affected workers in distressed communities. The interaction with corporate debt stress modeled in this paper would amplify total losses beyond what is shown here.

Calibration Approach

Default rates are calibrated to the GFC, using a borrower-level approach that decomposes economy-wide default rates into separate benchmarks for employed and unemployed borrowers, anchored to Gerardi et al.'s (2015) finding that unemployed borrowers were approximately three times as likely to default as employed borrowers.[64] Each debt category is modeled separately given its distinct risk profile, collateral structure, and default dynamics; for each scenario, the at-risk share of each category's outstanding balance is computed from the combined displaced and gig-transitioned workforce as a share of total nonfarm employment. For mortgages, the at-risk share is further adjusted to reflect homeownership rates among the affected population.

Default rates in each scenario are presented as a range. For displaced workers, the lower bound is anchored to the GFC default rate for unemployed borrowers; the higher bound applies an additional uplift to allow for the possibility that displacement under AI may be more severe. Unlike the GFC recession, which was largely cyclical and saw most workers re-employed at comparable wages within a year, AI displacement is likely to eliminate roles permanently across multiple sectors simultaneously. As Amodei predicts, re-employment may take substantially longer than in the GFC as AI advances faster than workers can retrain, and displaced knowledge workers who do find new work may downshift into lower-skilled, lower-paid roles—producing a structural wage loss that makes debt obligations harder to service even after re-employment. The 3–6 month savings runway assumed in conventional stress models offers little buffer: as of 2025, only 46% of US adults have enough emergency savings to cover three months of

[64] Kyle Gerardi, Kyle F. Herkenhoff, Lee E. Ohanian, and Paul S. Willen, "Unemployment, Negative Equity, and Strategic Default," Federal Reserve Bank of Boston Working Paper 15-13, 2015, https://www.bostonfed.org/publications/research-department-working-paper/2015/unemployment-negative-equity-and-strategic-default.aspx. Gerardi et al. found that unemployed borrowers were approximately three times as likely to default on mortgages as employed borrowers. This 3× multiplier is applied uniformly across all debt categories as a simplifying assumption; while empirical sensitivities may differ by asset class, applying a common multiplier provides a consistent framework for translating labor-market disruption into borrower-level distress.

expenses, suggesting that for the majority of displaced households, debt distress begins almost immediately upon income loss.[65]

For gig stressed workers, the lower bound is anchored to the GFC employed-borrower default rates; the higher bound allows for a modest uplift to account for more volatile income levels. Rates are applied only to the at-risk population's share of outstanding debt, not the full outstanding balance, and are blended across scenarios based on the composition of labor-market stress (the proportion of displaced workers and gig stressed workers). The full calibration methodology, including benchmark derivations and the low/high anchor framework, is detailed in the Appendices.

Mortgages

Outstanding US mortgage debt totals approximately $13.2 trillion, roughly 70% of the $18.8 trillion in total household debt, making it by far the largest single channel of household credit exposure.[66] Mortgage exposure is highly concentrated among middle- and upper-income households, with homeownership rates varying significantly by age and income cohort. The at-risk mortgage population is estimated by applying an effective homeownership rate of approximately 52% to the combined pool of workers displaced in excess of the 4.4% unemployment baseline, and gig-transitioned workers, reflecting the lower homeownership rates of younger, AI-exposed cohorts.[67] Table 9 summarizes estimated mortgage defaults across the four scenarios.

Table 9: Estimated Mortgage Defaults by Scenario ($13.2T outstanding)

Scenario	Mortgages at Risk (homeowners)	Distressed Mortgage Volume	Default Rate	Mortgage Defaults
Light	8.2M	$1.2T	7.57–8.70%	$93.6–107.7B
Moderate	10.0M	$1.5T	19.10–19.37%	$288.5–292.5B
High	12.4M	$1.9T	20.76–24.86%	$387.0–463.5B
Aggressive	14.9M	$2.2T	21.68–30.23%	$486.4–678.1B

[65] Bankrate, '2026 Annual Emergency Savings Report,' February 4, 2026, https://www.bankrate.com/banking/savings/emergency-savings-report/; Board of Governors of the Federal Reserve System, 'Report on the Economic Well-Being of U.S. Households in 2024 — Savings and Investments,' May 2025, https://www.federalreserve.gov/publications/2025-economic-well-being-of-us-households-in-2024-savings-and-investments.htm.

[66] Federal Reserve Bank of New York, "Quarterly Report on Household Debt and Credit, 2025:Q4," Center for Microeconomic Data, released February 2026, https://www.newyorkfed.org/microeconomics/hhdc

[67] The national homeownership rate is 65.7% (U.S. Census Bureau, CPS/Housing Vacancy Survey, Q4 2025, https://www.census.gov/housing/hvs/index.html), but the at-risk population is disproportionately composed of younger and early-career workers who exhibit substantially lower homeownership rates — approximately 37.9% for individuals under 35 (Census HVS, Q4 2025). The effective homeownership rate of approximately 51.8% is calibrated as the midpoint between these two benchmarks, capturing both the lower asset ownership of younger, AI-exposed workers and the partial offset from older displaced workers with higher mortgage exposure. Average outstanding mortgage balance is estimated at approximately $150,000; see Federal Reserve Bank of New York, Quarterly Report on Household Debt and Credit, Q4 2025 https://www.newyorkfed.org/microeconomics/hhdc; LendingTree analysis of NY Fed Consumer Credit Panel, Q3 2025.

For comparison, the GFC involved roughly $1.3 trillion in subprime mortgage exposure within an approximately $10 trillion residential mortgage market.[68] The Mortgage Bankers Association (MBA) serious delinquency rate peaked then at 9.1%; our model decomposes this into an employed-borrower default rate of 7.57% and a displaced-borrower rate of 22.70%.

These estimates capture direct defaults only. They do not account for geographic concentration of AI-exposed workers in high-value housing markets, negative equity spirals, or the wealth effect of declining home prices on broader consumer spending.

Credit Cards

Credit card debt is unsecured and is typically the first obligation dropped when income disappears or becomes volatile. Because credit card balances carry no collateral and lenders have limited recovery options, default rates among stressed borrowers are materially higher than for secured debt.

Table 10: Credit Card Defaults ($1.28T outstanding)

Scenario	Debt at Risk	Default Rate	Estimated Defaults
Light	$128B	9.11–10.48%	$11.7–13.4B
Moderate	$156B	23.00–23.32%	$35.9–36.4B
High	$193B	24.99–29.93%	$48.2–57.7B
Aggressive	$232B	26.11–36.40%	$60.6–84.5B

For comparison, the credit card charge-off rate peaked at approximately 11.0% during the GFC;[69] our model decomposes this into an employed-borrower rate of 9.11% and a displaced-borrower rate of 27.33%. Although credit card debt is unsecured and typically the first obligation borrowers stop servicing when income disappears, credit card default rates in these scenarios are not substantially higher than mortgage default rates—a counterintuitive result that reflects differences in how the GFC benchmarks are measured rather than differences in borrower behavior.[70]

---

[68] The U.S. residential mortgage market stood at approximately $10.5 trillion at the height of the GFC, per Federal Reserve Board, Financial Accounts of the U.S. (Z.1), Table L.218, https://www.federalreserve.gov/releases/z1/. The outstanding stock of subprime mortgages at the crisis peak is widely estimated at approximately $1.3 trillion; see, e.g., Board of Governors of the Federal Reserve System, "The Rise and Fall of the U.S. Mortgage and Housing Markets," and Federal Deposit Insurance Corporation, Crisis and Response: An FDIC History 2008–2019. The April 2008 IMF Global Financial Stability Report projected total credit-related losses at approximately $945 billion (rising to $1.4 trillion by October 2008), with an estimated $565 billion attributable to U.S. residential real-estate lending; see International Monetary Fund, Global Financial Stability Report: Containing Systemic Risks and Restoring Financial Soundness, April 2008, https://www.imf.org/en/Publications/GFSR/Issues/2016/12/31/Containing-Systemic-Risks-and-Restoring-Financial-Soundness.

[69] Board of Governors of the Federal Reserve System, 'Charge-Off Rate on Credit Card Loans, All Commercial Banks' (CORCCACBS), FRED, Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/CORCCACBS.

[70] The mortgage benchmark (MBA serious delinquency rate) is a stock measure — the share of all outstanding loans 90+ days delinquent or in foreclosure at a point in time — while the credit card benchmark (charge-off rate) is an annualized flow measure reflecting the rate at which balances were written off per year. Because mortgage defaults accumulate in the pipeline over years (borrowers can remain seriously delinquent for 12–18 months before foreclosure), the stock measure captures cumulative distress. Credit card defaults, by contrast, are typically charged off at 180 days and removed from the delinquent pool, so the flow rate understates cumulative crisis-period stress relative to the mortgage measure.

Auto Loans

Auto loans are secured by a depreciating asset, and borrowers tend to prioritize vehicle payments over other obligations to maintain transportation for job searching and re-employment—producing the lowest default rates of any consumer debt category across all scenarios. Forced sales by stressed borrowers would also depress used vehicle prices, increasing lender losses beyond headline default rates.

Table 11: Auto Loan Defaults ($1.67T outstanding)

Scenario	Debt at Risk	Default Rate	Estimated Defaults
Light	$167B	1.99–2.29%	$3.3–3.8B
Moderate	$204B	5.03–5.10%	$10.3–10.4B
High	$252B	5.47–6.55%	$13.8–16.5B
Aggressive	$303B	5.71–7.96%	$17.3–24.1B

For comparison, the auto loan charge-off rate peaked at approximately 2.4% during the GFC;[71] our model decomposes this into an employed-borrower rate of 1.99% and a displaced-borrower rate of 5.98%.

Student Loans

Student loan default dynamics differ structurally from other consumer debt. Federal student loans comprise approximately 92% of the $1.67 trillion in outstanding student debt, and include income-driven repayment (IDR) options that can lower monthly payments to $0 during periods of income loss—a flexibility not available to credit card or auto loan borrowers.[72] However, this protection has limits: extended unemployment eventually exhausts deferment and forbearance options, and private student loans (~8% of total, approximately $130 billion) offer no such protections.

Table 12: Student Loan Defaults ($1.66T outstanding)

Scenario	Debt at Risk	Default Rate	Estimated Defaults
Light	$166B	14.62–16.81%	$24.3–27.9B
Moderate	$203B	31.99–37.41%	$64.8–75.8B
High	$250B	43.73–48.02%	$109.4–120.1B
Aggressive	$301B	55.45–58.40%	$166.9–175.8B

[71] The auto loan charge-off benchmark of 2.4% is estimated from the Federal Reserve's broader 'Other Consumer Loans' charge-off series (FRED, CORCACBS), which peaked at 3.36% in Q4 2009. Auto loans, as secured obligations, exhibit lower charge-off rates than the unsecured components of this composite; the 2.3% estimate reflects this adjustment. See Federal Reserve Board, 'Charge-Off and Delinquency Rates on Loans and Leases at Commercial Banks,' https://www.federalreserve.gov/releases/chargeoff/.

[72] Federal Student Aid, U.S. Department of Education, *Federal Student Loan Portfolio*, Federal Student Aid Data Center, June 2025, https://studentaid.gov/data-center/student/portfolio (reporting $1.67 trillion in outstanding federal student loans); MeasureOne, *Private Student Lending Report*, 2025 (reporting approximately $130 billion in outstanding private student loans). The 92% federal share is derived by dividing the federal balance by total outstanding student debt (federal plus private). For income-driven repayment plans and eligibility, see Federal Student Aid, Income-Driven Repayment Plans, U.S. Department of Education, https://studentaid.gov/manage-loans/repayment/plans/income-driven. https://studentaid.gov/data-center/student/portfolio

Default rates for student loans are substantially higher than for other consumer debt categories across all scenarios. This reflects a number of factors. First, the baseline serious delinquency rate (90+ days delinquent or in default) is already elevated at 9.4% as of Q3 2025, following the resumption of post-pandemic reporting to credit bureaus.[73] The crisis-era benchmark itself is higher: unlike other consumer debt, student loan delinquency did not peak in 2008 to subsequently recover, but remained steadily high afterward—reaching 17.6% of borrowers seriously delinquent or in default by 2012 and remaining above 14% until the 2020 pandemic forbearance.[74] Our model decomposes this into an employed-borrower rate of 14.62% and a displaced-borrower rate of 43.85%. In addition, student loans cannot be discharged in bankruptcy, meaning distressed borrowers have no exit: they either eventually repay, default, or remain in perpetual delinquency, concentrating losses rather than distributing them through the credit system. The five-year default rate for the 2010 repayment cohort—borrowers who entered the labor market at peak unemployment—reached 23%.[75]

This persistent, structural pattern of distress driven by borrowers graduating into a weak labor market with non-dischargeable debt is a close analogue to AI displacement than the cyclical peak-and-recovery dynamics of mortgages or credit cards. Under AI displacement, with longer unemployment durations, permanent wage downgrades, and early-career workers disproportionately affected—precisely the cohort carrying the highest student debt burdens and the least labor-market cushion—substantially higher default rates are plausible. The High and Aggressive scenarios, in which over 40% of at-risk balances default, are consistent with these dynamics.

2.2 Corporate Debt Defaults

US nonfinancial corporate debt stands at approximately $14.1 trillion.[76] Corporate leverage varies significantly by sector, with debt-to-capital ratios ranging from 10–20% in less leveraged industries to 48–82% in more highly leveraged ones.[77] The ultimate impact of AI-driven consumption contraction on corporate debt markets will depend in part on which sectors bear the greatest displacement. If AI disproportionately affects industries at the higher end of this leverage spectrum, default rates could substantially exceed the economy-wide averages modeled below.

---

[73] Federal Reserve Bank of New York, "Household Debt Balances Grow Steadily; Mortgage Originations Tick Up in Third Quarter," press release, November 5, 2025, https://www.newyorkfed.org/newsevents/news/research/2025/20251105.

[74] Andrew Haughwout, Donghoon Lee, Daniel Mangrum, Joelle Scally, and Wilbert van der Klaauw, 'Student Loan Balance and Repayment Trends Since the Pandemic Disruption,' Federal Reserve Bank of New York, Liberty Street Economics, March 2025, https://libertystreeteconomics.newyorkfed.org/2025/03/student-loan-balance-and-repayment-trends-since-the-pandemic-disruption/.

[75] Rajashri Chakrabarti, Nicole Gorton, Michelle Jiang, and Wilbert van der Klaauw, "Are Student Loan Defaults Cyclical? It Depends," *Liberty Street Economics* (blog), Federal Reserve Bank of New York, November 22, 2017, https://libertystreeteconomics.newyorkfed.org/2017/11/are-student-loan-defaults-cyclical-it-depends/.

[76] Board of Governors of the Federal Reserve System, 'Nonfinancial Corporate Business; Debt Securities and Loans; Liability, Level' (BCNSDODNS), FRED, Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/BCNSDODNS.

[77] Aswath Damodaran, 'Debt Fundamentals by Sector (US),' NYU Stern School of Business, January 2026, https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/dbtfund.html.

Corporate default rates are derived from two fundamental credit default assumptions—an investment-grade (IG) rate and a speculative-grade or high yield (HY) rate—blended at the economy-wide credit composition of approximately 70% IG and 30% HY.[78] Default rates for IG and HY in each scenario are calibrated as a function of both labor-market income stress and macroeconomic contraction (scenario-specific GDP decline), combined into a Corporate Stress Factor (CSF) that measures overall credit stress relative to the GFC benchmark. These same primitives also underpin the corporate bond loss estimates within retirement portfolios and insurance portfolios. The full calibration methodology, including the CSF construction, the low/high mapping framework, and the nonlinear scaling parameters, is detailed in the Appendices.

Table 13: Corporate Default Rates Primitives

	GFC Peak	Light	Moderate	High	Aggressive
IG Default Rate	0.42%	0.15%	0.49–0.51%	0.71–0.77%	1.08–1.22%
HY Default Rate	9.95%	6.33%	11.08–11.59%	14.07–15.95%	19.23–23.46%

For reference, at the peak of the GFC crisis, IG default rates reached approximately 0.42% and HY default rates approximately 9.95%, implying a blended corporate default rate of roughly 3.3%.[79]

Table 14: Corporate Debt—Blended Default Rates and Estimated Defaults ($14.1T outstanding)

Scenario	Blended Default Rate	Total Defaults ($)
Light	2.01%	$283B
Moderate	3.67–3.83%	$517–541B
High	4.71–5.32%	$665–751B
Aggressive	6.52–7.89%	$920B–1.1T

[78] We estimate the speculative-grade share of total U.S. nonfinancial corporate debt ($14.1 trillion) by aggregating the three principal sub-investment-grade debt markets: high-yield corporate bonds (~$1.4 trillion; Srinivasan Margabandu, 'Unlocking Opportunity in the Leveraged Loan Market,' State Street Global Advisors, November 2025, https://www.ssga.com/us/en/individual/insights/unlocking-opportunity-in-the-leveraged-loan-market); U.S. leveraged loans (~$1.55 trillion; PitchBook LCD, 'Leveraged Loans Cap Solid 2025 Despite Headwinds for Floating-Rate Assets,' January 7, 2026, https://pitchbook.com/news/articles/leveraged-loans-cap-solid-2025-despite-headwinds-for-floating-rate-assets, citing Morningstar LSTA US Leveraged Loan Index); and U.S. private credit (~$1.3 trillion; Federal Reserve, as cited in S&P Dow Jones Indices, 'Understanding and Tracking Leveraged Loans,' November 2025, https://www.spglobal.com/spdji/en/index-tv/article/understanding-and-tracking-leveraged-loans/). Total speculative-grade debt is therefore approximately $4.3 trillion, or roughly 30% of the $14.1 trillion total. The investment-grade remainder (~$9.8 trillion) includes investment-grade corporate bonds and traditional bank lending to creditworthy borrowers.

[79] S&P Global Ratings, '2019 Annual Global Corporate Default and Rating Transition Study,' April 2020, available at https://maalot.co.il/Publications/TS20200504110435.pdf. Investment-grade default rate of 0.42% (2008) and speculative-grade default rate of 9.95% (2009) represent the respective annual peaks during the crisis. Blended rate of approximately 3.3% calculated as (0.70 × 0.42%) + (0.30 × 9.95%) = 3.28%.

The Moderate scenario produces corporate defaults slightly above GFC levels despite matching its unemployment rate, because the Corporate Stress Factor incorporates gig-transition income loss—a channel absent from the GFC—alongside the GDP contraction modeled in Section 1. The High and Aggressive scenarios reflect not only greater displacement but also nonlinear credit deterioration: beyond the GFC stress benchmark, HY default rates scale more steeply than IG rates, reflecting higher leverage, operating risk, and sensitivity to revenue declines among speculative-grade issuers. This asymmetric behavior is consistent with historical experience, in which HY default rates increased several multiples more than IG rates during the GFC.

2.3 Corporate Bond Mark-to-Market Losses

Even corporate bonds that do not default suffer price declines when credit spreads widen during a crisis, as investors demand higher compensation for perceived credit risk. During the GFC, IG credit spreads peaked at approximately 625 basis points and HY spreads exceeded 2,100 basis points,[80] producing significant mark-to-market losses across both categories—even for issuers that did not default. The IG peak benchmark of 19.2% is based on the observed peak-to-trough price decline on the iShares iBoxx $ Investment Grade Corporate Bond ETF (LQD) from February 2007 to October 2008.[81] The HY benchmark of 34.5% is based on the maximum drawdown recorded by the MSCI USD High Yield Corporate Bond Index over the same crisis period.[82] These benchmarks capture price-based mark-to-market losses—the declines that appear on institutional portfolio statements, trigger regulatory capital thresholds, and impair pension funding ratios—rather than total return losses, which are partially offset by coupon income received during the drawdown period.

Mark-to-market losses are calibrated using the same Corporate Stress Factor (CSF) that we use to govern default rates and are only applied to publicly traded corporate bonds (~$11.5 trillion). Losses from those instruments are captured through the default channel. To avoid double-counting, MTM losses are applied only to the non-defaulting portion of outstanding bonds. The full calibration methodology, including the low/high framework and spread-widening parameters, is detailed in the Appendices.

[80] ICE BofA US Corporate Index OAS peaked at approximately 625 basis points; ICE BofA US High Yield Master II OAS peaked at 2,182 basis points, both in December 2008. See 'Credit Spreads Explained: OAS, IG vs HY & NNN Cap Rates (Q1 2026),' InvestmentGrade.com, https://investmentgrade.com/credit-spreads/.
[81] LQD price history from Digrin, https://www.digrin.com/stocks/detail/LQD/price. Pre-crisis peak: $108.43 (February 2007); crisis trough: $87.65 (October 2008); price-only decline: 19.2%. On a total return basis (using dividend-adjusted prices of $50.64 and $44.81 respectively), the drawdown was approximately 11.5%, reflecting the partially offsetting effect of approximately 5–6% annual coupon income over the drawdown period. The price-based measure is used as the MTM benchmark because it reflects the portfolio valuation impact relevant to institutional balance sheets, funding ratios, and regulatory capital calculations.
[82] MSCI, 'MSCI USD High Yield Corporate Bond Index Factsheet,' March 31, 2026, https://www.msci.com/documents/1296102/3b44678f-06e3-018d-62ce-d4ae234a345f. Maximum drawdown of 34.48% from May 29, 2007 to December 15, 2008. Note that this index was launched June 29, 2020; pre-launch data is back-tested.

Table 15: Corporate Bond Mark-to-Market Rate Primitives

Metric	GFC Peak	Light	Moderate	High	Aggressive
IG MTM Rate	19.2%	5.72%	19.20–20.46%	19.20–23.81%	19.20–29.58%
HY MTM Rate	34.48%	10.27%	34.48–36.75%	34.48–42.75%	34.48–53.12%

Table 16: Corporate Bond Mark-to-Market Losses ($11.5T publicly traded)

Scenario	Non-Defaulting Exposure	Blended MTM Rate (70/30 IG/HY)	MTM Losses
Light	~$11.2T	7.08%	$795B
Moderate	~$11.0T	23.78–25.35%	$2.6–2.8T
High	~$10.8T	23.78–29.49%	$2.6–3.2T
Aggressive	~$10.5T	23.78–36.64%	$2.5–3.8T

The low case caps MTM losses at the GFC benchmark across all scenarios, reflecting the possibility that post-GFC policy frameworks and market structure changes may limit spread overshooting.[83] The high case allows losses to exceed GFC levels under severe stress, reflecting the potential for nonlinear liquidity withdrawal—the GFC experience showed spreads gapping wider than fundamentals alone would predict, driven by forced selling, counterparty fear, and the disappearance of market-making capacity.[84]

2.4 Equity Market Decline

US equity market capitalization is approximately $69 trillion as of December 31, 2025.[85] Equity market losses are driven by two reinforcing channels. First, when household income and consumption fall, corporate revenues decline—and because firms carry fixed costs (rent, debt service, salaries of retained employees), the earnings impact is amplified beyond the revenue decline through operating leverage. Second, as economic uncertainty rises and financial conditions tighten, investors apply lower price-to-earnings multiples to those reduced earnings, compressing valuations further. Because stock price equals earnings multiplied by the P/E ratio, these two channels compound multiplicatively.[86]

[83] In March 2020, the Federal Reserve established the Primary Market Corporate Credit Facility (PMCCF) and the Secondary Market Corporate Credit Facility (SMCCF) to support credit markets during the COVID-19 crisis, purchasing both individual corporate bonds and corporate bond ETFs. The announcement alone — before any significant purchases were executed — was sufficient to arrest the spread widening and reverse much of the mark-to-market decline in IG and HY corporate bonds. This precedent suggests that the Federal Reserve, acting as a 'dealer of last resort,' may have the capacity to set an effective floor on corporate bond prices under future stress scenarios, potentially capping MTM losses near 2008 levels even if underlying credit fundamentals deteriorate beyond that benchmark. See Nina Boyarchenko, Anna Kovner, and Or Shachar, 'It's What You Say and What You Buy: A Holistic Evaluation of the Corporate Credit Facilities,' Federal Reserve Bank of New York Staff Reports No. 935, revised January 2022, https://www.newyorkfed.org/research/staff_reports/sr935. However, the capacity for such interventions is not unlimited. Repeated use of emergency credit facilities raises concerns about moral hazard, central bank balance sheet expansion, and the political sustainability of backstopping private credit markets, particularly if the underlying cause of stress is structural displacement rather than a temporary liquidity shock.

[84] MTM rates are calculated separately for IG (benchmark = 19.2%) and HY (benchmark = 34.5%) using the CSF, then blended at economy-wide weights (70% IG / 30% HY). In the Light scenario, the CSF is below 1.0 and the low and high cases are identical. See Appendix B.4 for the full calibration framework.

[85] "Siblis Research, 'Total Market Value of U.S. Stock Market,' accessed May 2026, https://siblisresearch.com/data/us-stock-market-value/.

[86] Earnings decline and valuation compression compound multiplicatively, not additively. Stock price equals earnings multiplied by the price-to-earnings multiple; if earnings fall 30% (to 0.70× original) and the multiple compresses 20% (to 0.80× original), the resulting price is 0.70 × 0.80 =

The GFC provides the empirical anchor for both channels. Trailing 12-month S&P 500 operating earnings per share peaked at $91.47 (Q2 2007) and had declined to $49.51 by Q4 2008—the most recently reported earnings at the time the S&P 500 reached its price trough of 676 on March 6, 2009—an earnings contraction of approximately 46%.[87] The S&P 500 itself fell 57% peak-to-trough (October 2007 to March 2009).[88] The difference between the 46% earnings decline and the 57% price decline is attributable to a valuation multiple compression of approximately 20%.[89] The calibration framework scales each channel separately—earnings decline scales with scenario-specific consumption contraction, valuation compression scales with overall economic stress (CSF)—and recombines them multiplicatively. Low and high estimates reflect uncertainty in operating leverage and valuation sensitivity, particularly in severe scenarios where both effects intensify. The full methodology is detailed in the Appendices.

Table 17: Public Equity Market Decline Estimates ($69T market capitalization)

Scenario	Equity Decline (%)	Loss ($T)
Light	19.7–25.0%	$13.6–17.2T
Moderate	59.9–60.9%	$41.3–42.0T
High	71.3–83.6%	$49.2–57.7T
Aggressive	83.1–95.6%	$57.4–66.0T

The Light scenario produces a correction comparable to a moderate bear market. The Moderate scenario approximates the GFC experience—consistent with matching its unemployment rate and slightly exceeding its credit stress. The High and Aggressive scenarios represent progressively more severe drawdowns reflecting the unprecedented scale and structural nature of AI-driven displacement, in which operating leverage and valuation compression amplify each other under sustained demand contraction. The high end of the Aggressive scenario (95.6%) should be understood as a theoretical upper bound—it implies near-total destruction of equity value, exceeding even the Great Depression peak-to-trough

0.56× original — a 44% decline, not 50%. This multiplicative structure means that the combined equity market decline is always less than the simple sum of the two components.

[87] S&P Dow Jones Indices, 'S&P 500 Earnings and Estimate Report,' quarterly data, https://www.spglobal.com/spdji/en/documents/additional-material/sp-500-eps-est.xlsx. Trailing 12-month operating EPS are computed by summing four consecutive quarters from the 'Quarterly Data' sheet, column B (Operating Earnings Per Share). The peak of $91.47 reflects Q3 2006 ($23.03) + Q4 2006 ($21.99) + Q1 2007 ($22.39) + Q2 2007 ($24.06). The $49.51 figure reflects Q1 2008 ($16.62) + Q2 2008 ($17.02) + Q3 2008 ($15.96) + Q4 2008 (−$0.09). Q4 2008 operating EPS was essentially zero, reflecting the acute phase of the GFC.

[88] Federal Reserve History, 'The Great Recession,' Federal Reserve Bank of St. Louis, https://www.federalreservehistory.org/essays/great-recession-of-200709.

[89] The 20% multiple compression is derived residually from the observed price decline and the measured earnings contraction. Stock price equals earnings per share multiplied by the price-to-earnings multiple, so total price decline = $1 - (1 - E)(1 - M)$, where E is the earnings decline and M is the multiple compression. The S&P 500 declined 56.8% peak-to-trough, and trailing operating EPS declined 45.9% over the same period. Solving for $M = 1 - (0.432 \div 0.541) = 20.2\%$. This is confirmed directly by the observed P/E ratios: 17.1× at the October 2007 peak ($1,565 ÷ $91.47) compressing to 13.7× in March 2009 ($676 ÷ $49.51), a decline of 20.2%.

decline of approximately 89%.[90] In practice, policy intervention, residual earnings capacity in non-exposed sectors, and market-clearing dynamics would likely prevent a decline of this magnitude. But the figure illustrates the severity of the modeled stress environment and the scale of the risk absent structural intervention.

2.5 Pension and Retirement Crisis

Total US retirement assets were $49.1 trillion as of December 31, 2025, comprising $19.2 trillion in IRAs, $14.2 trillion in employer-sponsored defined contribution plans (of which $10.1 trillion in 401(k)s), $10.0 trillion in government defined benefit (DB) plans, $3.1 trillion in private-sector DB plans, and $2.6 trillion in annuity reserves.[91] We estimate that approximately 52.8% of total retirement assets (~$25.9 trillion) is allocated to public equities and approximately 23.1% (~$11.3 trillion) to fixed income, with the remaining ~24.1% in cash equivalents, alternative investments, and other assets. No single published source reports a complete asset-class decomposition for the full $49.1 trillion retirement market; these estimates are constructed by applying the best available allocation data for each retirement vehicle and, where no directly published aggregate exists, computing weighted averages across constituent sub-pools. See the Appendices for the full breakdown and sources.[92]

We estimate retirement asset losses through three simultaneous channels: equity market decline, fixed income impairment (corporate bond defaults, corporate bond spread widening, and government bond interest rate risk), and reduced employer and employee contributions. The first two channels reflect point-in-time portfolio losses; the third captures cumulative inflow shortfalls over a five-year horizon. Corporate bond losses apply the default rates and spread-widening framework we detail elsewhere, adjusted for retirement portfolios' credit mix of approximately 87% IG and 13% HY. Government bond losses use a duration-based approximation calibrated to fiscal-stress-driven rate increases. Equity losses reflect the same market declines applied throughout the report. Detailed sub-channel tables, rate derivations, and the government bond MTM calibration are provided in the Appendices.

Retirement asset losses are compounded by reduced inflows. Displaced workers with zero income cease both their own and their employer's contributions entirely, and financially stressed companies suspend or reduce matching for remaining employees. Workers reclassified into gig or contract status lose employer-sponsored contributions altogether and reduce their own in proportion to their lower income.

---

[90] See 'Closing Milestones of the Dow Jones Industrial Average,' Wikipedia, https://en.wikipedia.org/wiki/Closing_milestones_of_the_Dow_Jones_Industrial_Average; see also Federal Reserve History for broader context of the Great Depression, https://www.federalreservehistory.org/essays/great-depression.

[91] Investment Company Institute, 'Quarterly Retirement Market Data, Fourth Quarter 2025', https://www.ici.org/statistical-report/ret_25_q4.

[92] Estimates are derived from ICI asset allocation surveys, EBRI Issue Briefs, Federal Reserve Z.1 Financial Accounts, and NASRA Public Fund Survey data. See Appendix C.1 for vehicle-by-vehicle breakdown and sources.

This second mechanism is the sole driver of contribution shortfalls in the Light scenario, where no workers are displaced but approximately 15.8 million shift to lower-paid, non-benefited employment. We estimate this effect over a five-year horizon to capture the cumulative impact of sustained structural transformation. Match suspension rates are calibrated to the GFC using Form 5500 data on employer contribution suspensions; see the Appendices for the calibration methodology and detailed breakdown.

Table 18: Total Retirement Asset Losses by Channel ($49.1T outstanding)

Scenario	Equity Losses	Fixed Income Losses	Reduced Contributions (5-yr)	Total Losses
Light	$5.1–6.5T	$0.3–0.5T	$0.19–0.20T	$5.6–7.2T
Moderate	$15.6–15.8T	$1.0–1.3T	$0.35–0.39T	$17.0–17.6T
High	$18.6–21.8T	$1.3–1.9T	$0.51–0.56T	$20.4–24.2T
Aggressive	$21.6–24.9T	$1.6–2.3T	$0.66–0.73T	$23.9–27.9T

Defined-Benefit Plan Funding Impact

The losses above span all retirement assets—IRAs, 401(k)s, and other DC plans alongside DB pensions. For individual account holders in DC plans, the losses reduce personal wealth but create no systemic obligation: account balances simply decline. DB plans face a distinct and more dangerous risk, because they promise specific future payments to retirees regardless of what happens to plan assets. When assets fall, the gap between what plans owe and what they hold widens—creating unfunded liabilities that must eventually be covered by plan sponsors, taxpayers, or benefit reductions.

US DB plans—private-sector plans insured by the PBGC, plus federal, state, and local government pension systems—hold combined assets of approximately $13.1 trillion (approximately 27% of total $49.1 trillion US retirement assets).[93] At the present time, private-sector DB plans are approximately 97% funded,[94] but state and local government plans are only approximately 77% funded.[95] Against estimated combined liabilities of roughly $16.6 trillion,[96] the existing aggregate underfunding gap is approximately $3.5 trillion—before any further technology-driven displacement occurs. To estimate the impact on DB plans specifically, we apply the 27% DB share to the total retirement asset losses modeled above. The table below illustrates the resulting funding ratios under each scenario, assuming liabilities remain constant:

[93] Investment Company Institute, 'Quarterly Retirement Market Data, Fourth Quarter 2025', https://www.ici.org/statistical-report/ret_25_q4. Government DB: $10.0 trillion; Private-Sector DB: $3.1 trillion.
[94] Milliman, Inc., "Multiemployer Pension Funding Study: Year-End 2024" (February 2025), https://www.milliman.com/en/insight/multiemployer-pension-funding-study-year-end-2024.
[95] National Association of State Retirement Administrators, "Public Fund Survey Summary of Findings for FY 2024" (NASRA, 2025), https://www.nasra.org/publicfundsurvey.
[96] Board of Governors of the Federal Reserve System (US), "Defined Benefit Pension Funds; Pension Entitlements (Total Liabilities), Level," FRED, Federal Reserve Bank of St. Louis, series BOGZ1FL594190045Q, updated March 19, 2026, https://fred.stlouisfed.org/series/BOGZ1FL594190045Q.

Table 19: Defined-Benefit Funding Impact

Scenario	DB Asset Losses (27% of total)	Remaining DB Assets	Funding Ratio
Light	$1.5–1.9T	$11.2–11.7T	67–70%
Moderate	$4.5–4.6T	$8.5–8.6T	51–52%
High	$5.4–6.4T	$6.7–7.7T	41–47%
Aggressive	$6.3–7.3T	$5.8–6.8T	35–41%

These estimates could understate the severity of DB funding deterioration. The table above assumes that liabilities remain constant at approximately $16.6 trillion, but pension liabilities are valued as the present value of future benefit payments. In a crisis of this magnitude, the Federal Reserve would likely cut interest rates aggressively, as it did during the GFC. Lower rates would reduce the discount rate used to value pension obligations, mechanically increasing measured liabilities. These shortfalls could require some combination of Pension Benefit Guaranty Corporation backstops, federal support, and benefit reductions.

2.6 Insurance Industry Exposure

US insurance companies hold approximately $9.0 trillion in cash and invested assets.[97] Bonds comprise the largest share at 60.4% ($5.4 trillion), followed by equities at 13.1% ($1.2 trillion) and mortgage loans at 9.1% ($821 billion). Bond credit quality is high: 95.1% of holdings carry IG ratings, with only 4.9% HY.[98] Within the bond portfolio, approximately $3.0 trillion is in corporate bonds and $2.4 trillion in government and agency securities.[99]

We estimate insurance asset impairment across five sub-channels, structured to parallel the fixed income and equity methodology used throughout this report: corporate bond defaults, corporate bond mark-to-market losses from spread widening, government bond mark-to-market losses from interest rate risk, equity portfolio losses, and mortgage and real estate impairment. The bond portfolio methodology applies the same default rates and mark-to-market framework used in the pension section, adjusted for the insurance industry's higher credit quality (95/5 IG/HY versus 87/13 in retirement portfolios). Equity losses reflect the same market declines applied throughout the report, and mortgage/real estate impairment rates are anchored to our mortgage analysis, with additional stress from AI-driven commercial real estate vacancy increases. Detailed sub-channel tables and rate derivations are provided in the Appendices.

---

97 Michele Wong, "U.S. Insurance Industry's Cash and Invested Assets Rise Over 5% to Close in on $9 Trillion as of Year-End 2024," NAIC Capital Markets Bureau Special Report (National Association of Insurance Commissioners, May 2025), https://content.naic.org/sites/default/files/capital-markets-special-reports-asset-mix-ye2024.pdf.
98 Wong, "U.S. Insurance Industry's Cash and Invested Assets."
99 Wong, "U.S. Insurance Industry's Cash and Invested Assets."

Table 20: Consolidated Insurance Impairment

Scenario	Bond Losses	Equity Losses	Mortgage/RE Losses	Total Impairment
Light	**$157–235B**	$237–299B	$33–74B	$427–608B
Moderate	**$334–526B**	$719–731B	$82–148B	$1.1–1.4T
High	**$534–836B**	$856B–1.0T	$131–222B	$1.5–2.1T
Aggressive	**$770B–1.1T**	$998B–1.1T	$181–287B	$1.9–2.5T

These estimates capture direct asset impairment only and should be understood as a floor. They do not account for second-order effects: impaired insurers tightening credit or reducing reinsurance capacity; compounding pressure from bank balance sheet deterioration; or operational strain from higher health utilization, disability claims, and a shrinking premium base as unemployed workers reduce coverage. These dynamics would amplify the asset-side losses quantified above but are excluded due to insufficient data to produce credible bounds.

2.7 Social Security Acceleration

Social Security payroll tax losses are driven by two mechanisms. First, displaced workers cease earning taxable wages entirely, eliminating both the employer and employee shares of the combined 12.4% payroll tax rate.[100] Second, although gig-reclassified workers remain subject to equivalent payroll taxation through self-employment tax (SECA), their reduced wages shrink the taxable base, producing a net revenue loss proportional to the wage haircut. As of year-end 2024, the combined OASI and DI Trust Funds held reserves of $2.72 trillion, with projected depletion in 2034 under current assumptions.[101] The additional payroll tax losses modeled here would accelerate that timeline by reducing annual inflows against a reserve base already drawing down at an average rate of approximately $302 billion per year. See the Appendices for the derivation of acceleration estimates.

[100] Internal Revenue Service, "Topic No. 751, Social Security and Medicare Withholding Rates," accessed May 2026, https://www.irs.gov/taxtopics/tc751.

[101] Board of Trustees, Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds, The 2025 Annual Report of the Board of Trustees (Washington, DC: Social Security Administration, June 2025), https://www.ssa.gov/oact/tr/2025/. Trust fund reserves declined by $67 billion during 2024 to $2.72 trillion; total income was $1.42 trillion ($1.29 trillion in payroll taxes); total expenditures were $1.48 trillion.

Table 21: Social Security Payroll Tax Exposure by Scenario

	Light	Moderate	High	Aggressive
Workers Displaced	0	8.9M	16.8M	24.7M
Workers Gig-Shifted	15.8M	10.5M	7.1M	4.0M
Annual Payroll Tax Loss (Displacement)	$0	$75B	$141B	$208B
Annual Payroll Tax Loss (Gig Wage Haircut)	$20B	$18B	$15B	$10B
Total Annual Payroll Tax Loss	$20B	$92B	$156B	$218B
% of OASDI Annual Revenue (~$1.3T)	~1.6%	~7.2%	~12.1%	~16.9%
Estimated Trust Fund Depletion Acceleration	~0.6 yr	~2.1 yr	~3.1 yr	~3.8 yr

These acceleration estimates capture reduced inflows only. Early claiming by displaced workers would simultaneously increase outlays, compounding the effect; a precise projection incorporating both sides would require actuarial modeling beyond the scope of this report.

2.8 Tax Revenue and the Fiscal Doom Loop

Current federal revenue of approximately $5.2 trillion comprises individual income tax (approximately $2.6 trillion), payroll taxes (approximately $1.7 trillion), corporate income tax (approximately $452 billion), and other revenue (approximately $378 billion) as of FY2025.[102] Each major revenue stream is modeled independently using inputs derived elsewhere in the report.

Individual income tax losses are calculated by applying the average effective federal income tax rate of approximately 10% to the total annual income lost from displacement and gig reclassification.[103] Payroll tax losses are taken directly from §2.7. Corporate income tax declines are modeled through operating leverage: because corporate profits are a residual after largely fixed costs, a 1% decline in aggregate revenue produces a disproportionate decline in profits. With pre-tax corporate profit margins of approximately 11% of GDP, the implied operating leverage is roughly 8-9×.[104] We apply a conservative multiplier of 8×, well below the GFC precedent. During the GFC, corporate tax receipts fell from $370 billion (FY2007) to $138 billion (FY2009), a 63% decline, while real GDP contracted 4.3% peak to trough—

[102] Congressional Budget Office, "Monthly Budget Review: Summary for Fiscal Year 2025" (Washington, DC: CBO, 2024), https://www.cbo.gov/system/files/2025-11/61307-MBR-FY25-final.pdf
[103] Internal Revenue Service, "Federal Income Tax Rates and Brackets," updated February 2026, https://www.irs.gov/filing/federal-income-tax-rates-and-brackets. Effective rate of approximately 10% calculated for a single filer at the model's average displacement wage of $67,920 using 2025 brackets and the $15,000 standard deduction.
[104] U.S. Bureau of Economic Analysis, "National Income: Corporate Business: Corporate Profits Before Tax (without IVA and CCAdj)," FRED, Federal Reserve Bank of St. Louis, series E561RC1A027NBEA, https://fred.stlouisfed.org/series/E561RC1A027NBEA. Pre-tax corporate profits were approximately $3.7 trillion in 2024 against nominal GDP of approximately $29.3 trillion (FRED series GDP), yielding a pre-tax profit-to-GDP ratio of roughly 12.6%. Operating leverage is approximately 1 ÷ 0.126 ≈ 8×.

implying an effective multiplier of approximately 15×.[105] Other revenue—excise taxes, estate taxes, customs duties, and miscellaneous receipts—declines proportionally with GDP.

Table 22: Federal Revenue Decline by Source

Revenue Source	Current	Light	Moderate	High	Aggressive
Individual income tax	$2.6T	$2.6T (−1%)	$2.5T (−3%)	$2.5T (−5%)	$2.4T (−7%)
Payroll taxes	$1.71T	$1.7T (−1%)	$1.6T (−5%)	$1.6T (−9%)	$1.5T (−13%)
Corporate income tax	$452B	$415B (−8%)	$280B (−38%)	$161B (−65%)	$46B (−90%)
Other	$378B	$374B (−1%)	$360B (−5%)	$348B (−8%)	$336B (−11%)
Total	$5.2T	$5.1T (−2.6%)	$4.8T (−8.0%)	$4.5T (−12.8%)	$4.3T (−17.4%)
Total Revenue decline		−$137B (−2.6%)	−$417B (−8.0%)	−$664B (−12.8%)	−$903B (−17.4%)

Corporate income tax accounts for only 9% of the revenue base but drives a disproportionate share of the decline in the heavier scenarios due to operating leverage: under Aggressive displacement, corporate profits are nearly eliminated (90% decline), consistent with aggregate margins of ~12% being overwhelmed by an 11.2% GDP contraction. Income and payroll taxes, while declining by smaller percentages, represent larger absolute losses given their $4.3 trillion combined base.

These projections represent the initial-year impact as displacement takes hold and capture only direct, mechanically derived effects on workers and firms already modeled in this report. They do not include secondary effects on the remaining workforce—wage stagnation, reduced hours, and downward wage pressure from labor market slack—which would further erode the income and payroll tax base. The actual revenue decline is therefore likely larger than shown here, particularly in the heavier scenarios where labor market spillovers would be most pronounced.

Illustrative Compounding Dynamics: The Fiscal Doom Loop

These initial-year figures capture only direct effects on displaced and gig-reclassified workers and affected firms. Over a multi-year horizon, the feedback mechanisms described above—secondary wage effects, expenditure surges, debt service escalation, and contractionary fiscal responses—would deepen these declines substantially. Modeling the full compounding trajectory is an area for future work. Over a multi-year horizon, several feedback mechanisms would deepen the fiscal crisis. A precise projection would require macroeconomic modeling with behavioral responses, which is beyond the scope of this report. We note that the fiscal doom loop operates through **four** reinforcing channels:

[105] Congressional Budget Office, "Historical Budget Data," Table 2: Revenues by Major Source (February 2026), https://www.cbo.gov/data/budget-economic-data.

Revenue–deficit spiral. The initial revenue losses described above immediately widen the federal deficit. Even under the moderate scenario, the $400 billion revenue shortfall adds directly to annual borrowing, bringing the deficit above $2 trillion. Under the Aggressive scenario, the $900 billion shortfall increases the current deficit by roughly 50%, before any expenditure increases are factored in.

Expenditure surge. Revenue collapses at precisely the moment demand for public services surges. Unemployment insurance claims spike, healthcare costs rise (both through Medicaid expansion and stress-related morbidity), retraining programs are needed at unprecedented scale, and eventually pension system bailouts may require federal backstops. These expenditure pressures compound the deficit beyond what revenue losses alone would produce.

Debt service escalation. Rapidly accumulating debt increases annual interest payments. If fiscal stress also pushes up long-term borrowing costs—as occurred during the UK gilt crisis of 2022, when loss of fiscal credibility drove rates sharply higher—the interest burden accelerates further. Higher interest payments consume revenue that might otherwise fund countercyclical programs, reducing the government's ability to respond.

Contractionary feedback. If the government is forced into austerity (cutting spending or raising taxes on a shrinking base) to manage debt dynamics, those measures further suppress economic activity, which in turn reduces tax revenue further—completing the loop.

As a result, revenue losses that appear manageable in Year 1 become potentially catastrophic (e.g. by Year 7) as feedback loops compound. The result is a fiscal trajectory with no stable equilibrium absent dramatic intervention: rising debt drives higher interest costs, which drive larger deficits, which drive more debt. This is the dynamic that makes the case for preventive action—whether predistributive, redistributive, or both—before the loop becomes self-reinforcing.

2.9 The AI Revenue Reflexivity Trap

The global AI market is projected to grow from approximately $391–758 billion in 2025 to $3.5-4.3 trillion by the early/mid 2030s, depending on definitional scope.[106] These projections assume continued growth in enterprise adoption, consumer subscriptions, and digital advertising—all of which depend, directly or

[106] Estimates vary by source and definitional scope. Grand View Research estimates the global AI market at $391 billion in 2025, reaching $3.5 trillion by 2033 (Grand View Research, "Artificial Intelligence Market Size, Share & Trends Analysis Report," 2025, https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market). Precedence Research estimates $758 billion in 2025, reaching $4.2 trillion by 2035 (Precedence Research, "Artificial Intelligence Market Size, Share, and Trends 2026 to 2035," https://www.precedenceresearch.com/artificial-intelligence-market). The wide range reflects differences in definitional scope — narrower software-only definitions produce lower figures, while broader definitions including hardware, services, and embedded AI produce higher ones.

indirectly, on the same consumer spending that mass displacement would destroy. We term this contradiction the "AI revenue reflexivity trap."

The mechanism is straightforward. AI companies derive revenue primarily from enterprises, which in turn derive revenue from consumers. The consumption contractions modeled—ranging from 0.8% of GDP (Light) to 9.1% of GDP (Aggressive)—would weaken enterprise revenues across the economy, reducing both the ability and the willingness of firms to invest in AI. Consumer AI subscriptions, as discretionary expenditures, would face direct pressure from displaced and income-reduced households. During the GFC recession (2008–2009), when GDP contracted just 4.3%, global IT spending fell 6% and enterprise hardware investment fell over 16%.[107] The consumption contractions in our heavier scenarios are two to three times larger than the GFC, and AI—as a newer, more discretionary technology category—would likely prove more vulnerable than established IT spending.

There is a countervailing force: some firms may accelerate AI adoption during downturns to cut labor costs, partially offsetting the demand-side decline. However, this would simultaneously deepen displacement, reinforcing the underlying consumption problem.

The reflexive implication strengthens the case for cooperation. AI companies themselves have a direct financial interest in maintaining consumer purchasing power. Broad-based ownership is not merely sound social policy—it is a precondition for AI companies reaching the revenue scale their investors are pricing in. An AI industry that destroys its own customer base through displacement, without ensuring displaced workers retain income, undermines its own growth trajectory. This reflexivity also narrows the window for action: if equity structures are not established before the consumption decline begins, the falling profit base makes predistributive models less effective at precisely the moment they are most needed, while the shrinking tax base simultaneously makes redistribution more difficult.

[107] Denise Dubie, "Gartner Adjusts 2009 IT Spend Downward Again," Computerworld, July 7, 2009, https://www.computerworld.com/article/1552353/gartner-adjusts-2009-it-spend-downward-again.html. Global IT spending fell 6% in 2009 to $3.2 trillion; hardware declined 16.3%, software 1.6%, IT services 5.6%.

Attribution

Authors and contributors:

- Delilah Rothenberg, Co-founder & Executive Director
- Raphaele Chappe, PhD, Co-founding Partner & Director of Economic Research
- Juan Jardon, Associate Director, Investment Practices
- Shannon Mullins, Director of Operations
- With input from PDI's enterprise account with Anthropic's Claude

Contact: delilah@predistributioninitiative.org

Attribution: Please attribute any public references to this work to the Predistribution Initiative (PDI). The PDI team welcomes the opportunity to engage in discussions related to the fine-tuning and implementation of this analysis and proposal further. The concepts in this paper are not intended to be definitive or prescriptive, and PDI recognizes that further co-creation will likely result in improvements.

Accompanying Materials:

Interactive Excel model (forthcoming) with all equations, sources, and adjustable parameters.

Please see www.predistributioninitiative.org for additional papers from the Predistribution AI Lab.

References

Acemoglu, Daron. “The Simple Macroeconomics of AI.” Economic Policy 40, no. 121 (January 2025): 13–58. https://doi.org/10.1093/epolic/eiae042.

Acemoglu, Daron, and Pascual Restrepo. “Automation and New Tasks: How Technology Displaces and Reinstates Labor.” Journal of Economic Perspectives 33, no. 2 (Spring 2019): 3–30. https://doi.org/10.1257/jep.33.2.3.

Acemoglu, Daron, and Pascual Restrepo. “Tasks, Automation, and the Rise in U.S. Wage Inequality.” Econometrica 90, no. 5 (September 2022): 1973–2016. https://economics.mit.edu/sites/default/files/2022-10/Tasks%20Automation%20and%20the%20Rise%20in%20US%20Wage%20Inequality.pdf.

Amodei, Dario. “The Adolescence of Technology.” January 2026. https://www.darioamodei.com/essay/the-adolescence-of-technology.

Arnon, Alexander. “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/.

Auerbach, Alan J., and Yuriy Gorodnichenko. "Measuring the Output Responses to Fiscal Policy." American Economic Journal: Economic Policy 4, no. 2 (2012): 1–27.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. “The Fall of the Labor Share and the Rise of Superstar Firms.” Quarterly Journal of Economics 135, no. 2 (May 2020): 645–709. https://doi.org/10.1093/qje/qjaa004.

Bank for International Settlements. 87th Annual Report. June 2017.

Bankrate. “2026 Annual Emergency Savings Report.” February 4, 2026. https://www.bankrate.com/banking/savings/emergency-savings-report/.

Below, Łukasz. “The Gig Economy: A Tale of Two Labor Markets.” ADP Research Institute, November 20, 2025. https://www.adpresearch.com/the-gig-economy-a-tale-of-two-labor-markets/.

Blanchard, Olivier J., and Daniel Leigh. "Growth Forecast Errors and Fiscal Multipliers." IMF Working Paper No. 13/1. Washington, DC: International Monetary Fund, January 2013. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2226267.

Bloomberg. “Anthropic Attracts Investor Offers at an $800 Billion Valuation.” April 14, 2026. https://www.bloomberg.com/news/articles/2026-04-14/anthropic-attracts-investor-offers-at-a-800-billion-valuation.

Bloomberg. “Anthropic Tops $30 Billion Run Rate, Seals Broadcom Deal.” April 7, 2026. https://www.bloomberg.com/news/articles/2026-04-06/broadcom-confirms-deal-to-ship-google-tpu-chips-to-anthropic.

Board of Governors of the Federal Reserve System. “Charge-Off Rate on Credit Card Loans, All Commercial Banks” (CORCCACBS). FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/CORCCACBS.

Board of Governors of the Federal Reserve System. “Charge-Off and Delinquency Rates on Loans and Leases at Commercial Banks.” https://www.federalreserve.gov/releases/chargeoff/.

Board of Governors of the Federal Reserve System. “Defined Benefit Pension Funds; Pension Entitlements (Total Liabilities), Level.” FRED, series BOGZ1FL594190045Q. https://fred.stlouisfed.org/series/BOGZ1FL594190045Q.

Board of Governors of the Federal Reserve System. Distributional Financial Accounts of the United States. Updated March 27, 2026. https://www.federalreserve.gov/releases/z1/dataviz/dfa/distribute/chart/.

Board of Governors of the Federal Reserve System. Financial Accounts of the United States (Z.1), Table L.218. https://www.federalreserve.gov/releases/z1/.

Board of Governors of the Federal Reserve System. "Nonfinancial Corporate Business; Debt Securities and Loans; Liability, Level" (BCNSDODNS). FRED. https://fred.stlouisfed.org/series/BCNSDODNS.

Board of Governors of the Federal Reserve System. "Report on the Economic Well-Being of U.S. Households in 2024 — Savings and Investments." May 2025. https://www.federalreserve.gov/publications/2025-economic-well-being-of-us-households-in-2024-savings-and-investments.htm.

Board of Trustees, Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds. The 2025 Annual Report. Washington, DC: Social Security Administration, June 2025. https://www.ssa.gov/oact/tr/2025/.

Boyarchenko, Nina, Anna Kovner, and Or Shachar. "It's What You Say and What You Buy: A Holistic Evaluation of the Corporate Credit Facilities." Federal Reserve Bank of New York Staff Reports No. 935, revised January 2022. https://www.newyorkfed.org/research/staff_reports/sr935.

Briggs, Joseph, and Devesh Kodnani. "The Potentially Large Effects of Artificial Intelligence on Economic Growth." Goldman Sachs Global Investment Research, March 26, 2023. https://www.goldmansachs.com/insights/articles/generative-ai-could-raise-global-gdp-by-7-percent.

Brynjolfsson, Erik. Interview with NPR Planet Money. February 4, 2025. https://www.npr.org/sections/planet-money/2025/02/04/g-s1-46018/ai-deepseek-economics-jevons-paradox.

Brynjolfsson, Erik, Danielle Li Chandar, and Lindsey R. Chen. "Canaries in the Coal Mine? Early-Career Employment and AI Exposure." Working Paper, 2025. https://digitaleconomy.stanford.edu/app/uploads/2025/11/CanariesintheCoalMine_Nov25.pdf.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies." American Economic Journal: Macroeconomics 13, no. 1 (January 2021): 333–372. https://doi.org/10.1257/mac.20180386.

Chakrabarti, Rajashri, Nicole Gorton, Michelle Jiang, and Wilbert van der Klaauw. "Are Student Loan Defaults Cyclical? It Depends." Liberty Street Economics, Federal Reserve Bank of New York, November 22, 2017. https://libertystreeteconomics.newyorkfed.org/2017/11/are-student-loan-defaults-cyclical-it-depends/.

CNBC. "More Americans with College Degrees Are Working Multiple Jobs." March 16, 2025. https://www.cnbc.com/2025/03/16/more-americans-with-college-degrees-are-working-multiple-jobs.html.

Coase, Ronald H. "The Nature of the Firm." Economica 4, no. 16 (November 1937): 386–405.

Columbia Undergraduate Law Review. "Employee or Independent Contractor? A Legal Analysis of Uber's Worker Misclassification." September 2024. https://www.culawreview.org/current-events-2/employee-or-independent-contractor-a-legal-analysis-of-ubers-worker-misclassification.

Congressional Budget Office. "Historical Budget Data," Table 2: Revenues by Major Source. February 2026. https://www.cbo.gov/data/budget-economic-data.

Congressional Budget Office. “Monthly Budget Review: Summary for Fiscal Year 2025.” Washington, DC: CBO, 2024. https://www.cbo.gov/system/files/2025-11/61307-MBR-FY25-final.pdf.

Damodaran, Aswath. “Debt Fundamentals by Sector (US).” NYU Stern School of Business, January 2026. https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/dbtfund.html.

Dubie, Denise. “Gartner Adjusts 2009 IT Spend Downward Again.” Computerworld, July 7, 2009. https://www.computerworld.com/article/1552353/gartner-adjusts-2009-it-spend-downward-again.html.

Economic Policy Institute. “The Productivity–Pay Gap.” 2025. https://www.epi.org/productivity-pay-gap/.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock. “GPTs Are GPTs: Labor Market Impact Potential of LLMs.” Science 384, no. 6702 (June 21, 2024): 1306–1308. https://doi.org/10.1126/science.adj0998.

Emerson, Greg, Matthew Kropp, et al. “AI Will Reshape More Jobs Than It Replaces.” BCG Henderson Institute, April 3, 2026. https://www.bcg.com/publications/2026/ai-will-reshape-more-jobs-than-it-replaces.

Farrell, Diana, Fiona Greig, and Amar Hamoudi. “The Online Platform Economy in 2018: Drivers, Workers, Sellers, and Lessors.” JPMorgan Chase Institute, September 2019. https://www.jpmorganchase.com/institute/research/labor-markets/report-ope-2018.

Federal Reserve Bank of New York. “Household Debt Balances Grow Steadily; Mortgage Originations Tick Up in Third Quarter.” Press release, November 5, 2025. https://www.newyorkfed.org/newsevents/news/research/2025/20251105.

Federal Reserve Bank of New York. “Quarterly Report on Household Debt and Credit, 2025:Q4.” Center for Microeconomic Data, released February 2026. https://www.newyorkfed.org/microeconomics/hhdc.

Federal Reserve Bank of St. Louis. “The State of U.S. Household Wealth.” June 23, 2025. https://www.stlouisfed.org/open-vault/2025/june/the-state-of-us-household-wealth.

Federal Reserve History. “The Great Recession.” Federal Reserve Bank of St. Louis. https://www.federalreservehistory.org/essays/great-recession-of-200709.

Federal Student Aid, U.S. Department of Education. Federal Student Loan Portfolio. Federal Student Aid Data Center, June 2025. https://studentaid.gov/data-center/student/portfolio.

Fortune. “Anthropic CEO Dario Amodei Explains His Spending Caution.” February 14, 2026. https://fortune.com/2026/02/14/anthropic-ceo-dario-amodei-spending-capex-risk-ai-revenue-forecasts-bankruptcy/.

Fortune. “U.S. Workers Just Took Home Their Smallest Share of Capital Since 1947,” January 2026, https://fortune.com/2026/01/13/us-workers-smallest-labor-share-gdp-on-record/

Fortune Business Insights. “Artificial Intelligence Market Size & Growth, 2034.” https://www.fortunebusinessinsights.com/industry-reports/artificial-intelligence-market-100114.

Gerardi, Kyle, Kyle F. Herkenhoff, Lee E. Ohanian, and Paul S. Willen. “Unemployment, Negative Equity, and Strategic Default.” Federal Reserve Bank of Boston Working Paper 15-13, 2015. https://www.bostonfed.org/publications/research-department-working-paper/2015/unemployment-negative-equity-and-strategic-default.aspx.

Grand View Research. “Artificial Intelligence Market Size & Trends Report, 2033.” https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market.

Green, Michael W. "Part 1: My Life Is a Lie." Yes I Give a Fig (Substack), 2025/2026. https://www.yesigiveafig.com/p/part-1-my-life-is-a-lie.

Hacker, Jacob S. The Great Risk Shift: The New Economic Insecurity and the Decline of the American Dream. Rev. and exp. ed. New York: Oxford University Press, 2019.

Haughwout, Andrew, Donghoon Lee, Daniel Mangrum, Joelle Scally, and Wilbert van der Klaauw. "Student Loan Balance and Repayment Trends Since the Pandemic Disruption." Liberty Street Economics, Federal Reserve Bank of New York, March 2025. https://libertystreeteconomics.newyorkfed.org/2025/03/student-loan-balance-and-repayment-trends-since-the-pandemic-disruption/.

ICE BofA US Corporate Index and US High Yield Master II OAS. See "Credit Spreads Explained: OAS, IG vs HY & NNN Cap Rates (Q1 2026)." InvestmentGrade.com. https://investmentgrade.com/credit-spreads/.

Internal Revenue Service. "Federal Income Tax Rates and Brackets." Updated February 2026. https://www.irs.gov/filing/federal-income-tax-rates-and-brackets.

Internal Revenue Service. "Topic No. 751, Social Security and Medicare Withholding Rates." Accessed May 2026. https://www.irs.gov/taxtopics/tc751.

International Monetary Fund. Global Financial Stability Report: Containing Systemic Risks and Restoring Financial Soundness. April 2008. https://www.imf.org/en/Publications/GFSR/Issues/2016/12/31/Containing-Systemic-Risks-and-Restoring-Financial-Soundness.

Investment Company Institute. "Quarterly Retirement Market Data, Fourth Quarter 2025." https://www.ici.org/statistical-report/ret_25_q4.

Ip, Greg. "The Record Divide Between Corporate Profits and Worker Pay." *Wall Street Journal*, May 29, 2026. https://www.wsj.com/finance/stocks/the-record-divide-between-corporate-profits-and-worker-pay-ea4c75bc

Jackson, Emory, Adam Looney, and Shanthi Ramnath. "The Rise of Alternative Work Arrangements: Evidence and Implications for Tax Filing and Benefit Coverage." Office of Tax Analysis Working Paper 114, U.S. Department of the Treasury, 2017. https://home.treasury.gov/system/files/131/WP-114.pdf.

Jappelli, Tullio, and Luigi Pistaferri. "Fiscal Policy and MPC Heterogeneity." American Economic Journal: Macroeconomics 6, no. 4 (October 2014): 107–136. https://doi.org/10.1257/mac.6.4.107.

Jevons, William Stanley. The Coal Question: An Inquiry Concerning the Progress of the Nation, and the Probable Exhaustion of Our Coal-Mines. London: Macmillan, 1865.

Johnson, David S., Jonathan A. Parker, and Nicholas S. Souleles. "Household Expenditure and the Income Tax Rebates of 2001." American Economic Review 96, no. 5 (December 2006): 1589–1610. https://doi.org/10.1257/aer.96.5.1589.

JUST Capital. "New Research Reveals How Public Expectations on AI Are Shifting." 2026. https://justcapital.com/news/new-research-reveals-how-public-expectations-on-ai-are-shifting/.

Karger, Ezra, Otto Kuusela, et al. "Forecasting the Economic Effects of AI." Forecasting Research Institute, March 2026. https://www.nber.org/papers/w35046.

Katz, Lawrence F., and Alan B. Krueger. "The Rise and Nature of Alternative Work Arrangements in the United States, 1995–2015." ILR Review 72, no. 2 (2019): 382–416. https://journals.sagepub.com/doi/10.1177/0019793918820008.

Katz, Lawrence F., and Alan B. Krueger. “Understanding Trends in Alternative Work Arrangements in the United States.” RSF: The Russell Sage Foundation Journal of the Social Sciences 5, no. 5 (2019): 132–146. https://www.nber.org/system/files/working_papers/w25425/w25425.pdf.

Lazonick, William. “Profits Without Prosperity.” Harvard Business Review, September 2014. https://hbr.org/2014/09/profits-without-prosperity.

Lazonick, William, and Mary O’Sullivan. “Maximizing Shareholder Value: A New Ideology for Corporate Governance.” Economy and Society 29, no. 1 (2000): 13–35. https://doi.org/10.1080/030851400360541.

Leão, Emanuel, and Pedro Leão. “The Paradox of Investment: Why Investment Generates Excess Capacity in the Long Run.” Review of Political Economy, 2024.

Leswing, K. “Anthropic Closes $30 Billion Funding Round as Cash Keeps Flowing into Top AI Startups.” CNBC, February 12, 2026. https://www.cnbc.com/2026/02/12/anthropic-closes-30-billion-funding-round-at-380-billion-valuation.html.

LQD price history. Digrin. https://www.digrin.com/stocks/detail/LQD/price.

Margabandu, Srinivasan. “Unlocking Opportunity in the Leveraged Loan Market.” State Street Global Advisors, November 2025. https://www.ssga.com/us/en/individual/insights/unlocking-opportunity-in-the-leveraged-loan-market.

MarketsandMarkets. “Artificial Intelligence Market Report, 2025–2032.” https://www.marketsandmarkets.com/Market-Reports/artificial-intelligence-market-74851580.html.

McKinsey Global Institute. A Future That Works: Automation, Employment, and Productivity. January 2017. https://www.mckinsey.com/~/media/mckinsey/featured%20insights/digital%20disruption/harnessing%20automation%20for%20a%20future%20that%20works/mgi-a-future-that-works_in-brief.pdf.

McKinsey Global Institute. Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation. December 2017. https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages.

MeasureOne. Private Student Lending Report. 2025.

Milliman, Inc. “Multiemployer Pension Funding Study: Year-End 2024.” February 2025. https://www.milliman.com/en/insight/multiemployer-pension-funding-study-year-end-2024.

Mishel, Lawrence. “Uber and the Labor Market.” Economic Policy Institute, May 15, 2018. https://www.epi.org/publication/uber-and-the-labor-market-uber-drivers-compensation-wages-and-the-scale-of-uber-and-the-gig-economy/.

MSCI. “MSCI USD High Yield Corporate Bond Index Factsheet.” March 31, 2026. https://www.msci.com/documents/1296102/3b44678f-06e3-018d-62ce-d4ae234a345f.

Nadella, Satya. Cited in “Jevons Paradox: The 160-Year-Old Idea That Explains Why AI Is Creating More Jobs, Not Fewer.” Wholesale Investor, March 26, 2026. https://www.wholesaleinvestor.com/jevons-paradox-the-160-year-old-idea-that-explains-why-ai-is-creating-more-jobs-not-fewer/.

National Association of Insurance Commissioners. See Wong, Michele, below.

National Association of State Retirement Administrators. “Public Fund Survey Summary of Findings for FY 2024.” 2025. https://www.nasra.org/publicfundsurvey.

Pettis, Michael. “Excess Savings and Global Imbalances.” Carnegie Endowment for International Peace, 2016.

Philippon, Thomas. The Great Reversal: How America Gave Up on Free Markets. Cambridge, MA: Harvard University Press, 2019. https://www.hup.harvard.edu/books/9780674237544.

PIMCO. “Why U.S. Productivity Gains No Longer Reach Workers.” February 2026. https://www.pimco.com/us/en/insights/why-us-productivity-gains-no-longer-reach-workers.

PitchBook LCD. “Leveraged Loans Cap Solid 2025 Despite Headwinds for Floating-Rate Assets.” January 7, 2026. https://pitchbook.com/news/articles/leveraged-loans-cap-solid-2025-despite-headwinds-for-floating-rate-assets.

Precedence Research. “Artificial Intelligence Market Size, 2025–2035.” https://www.precedenceresearch.com/artificial-intelligence-market.

S&P Dow Jones Indices. “S&P 500 Earnings and Estimate Report.” Quarterly data. https://www.spglobal.com/spdji/en/documents/additional-material/sp-500-eps-est.xlsx.

S&P Global Ratings. “2019 Annual Global Corporate Default and Rating Transition Study.” April 2020. https://maalot.co.il/Publications/TS20200504110435.pdf.

Siblis Research. “Total Market Value of U.S. Stock Market.” Accessed May 2026. https://siblisresearch.com/data/us-stock-market-value/.

SIFMA Research. “Research Quarterly: Fixed Income — Outstanding.” March 20, 2026. https://www.sifma.org/research/statistics/research-quarterly-fixed-income-outstanding.

Slok, Torsten. “The Jevons Employment Effect From AI.” The Daily Spark (Apollo), April 28, 2026. https://www.apollo.com/wealth/the-daily-spark/the-jevons-employment-effect-from-ai.

S&P Dow Jones Indices / S&P Global. “Understanding and Tracking Leveraged Loans.” November 2025. https://www.spglobal.com/spdji/en/index-tv/article/understanding-and-tracking-leveraged-loans/.

Statista. “Artificial Intelligence — Worldwide Market Forecast.” https://www.statista.com/topics/3104/artificial-intelligence-ai-worldwide/.

U.S. Bureau of Economic Analysis. “National Income: Corporate Business: Corporate Profits Before Tax (without IVA and CCAdj).” FRED, series E561RC1A027NBEA. https://fred.stlouisfed.org/series/E561RC1A027NBEA.

U.S. Bureau of Economic Analysis. “Shares of Gross Domestic Product: Personal Consumption Expenditures” (DPCERE1Q156NBEA). FRED, Q4 2025. https://fred.stlouisfed.org/series/DPCERE1Q156NBEA.

U.S. Bureau of Labor Statistics. “Current Employment Statistics, Nonfarm Payroll Employment.” January 2026 (benchmark-revised). https://www.bls.gov/news.release/empsit.nr0.htm.

U.S. Bureau of Labor Statistics. “Labor Share of Output Has Declined Since 1947.” The Economics Daily, March 7, 2017. https://www.bls.gov/opub/ted/2017/labor-share-of-output-has-declined-since-1947.htm.

U.S. Bureau of Labor Statistics. “Occupational Employment and Wage Statistics (OEWS), May 2024.” https://data.bls.gov/oes/.

U.S. Bureau of Labor Statistics, "Productivity and Costs, First Quarter 2026, Preliminary," news release USDL-26-0835, May 7, 2026, https://www.bls.gov/news.release/archives/prod2_05072026.htm

U.S. Bureau of Labor Statistics. “The Employment Situation—October 2009.” USDL-09-1331, November 6, 2009. https://www.bls.gov/news.release/archives/empsit_11062009.pdf.

U.S. Bureau of Labor Statistics. “Worker Displacement: 2007–2009.” USDL101174, August 26, 2010. https://www.bls.gov/news.release/archives/disp_08262010.htm.

U.S. Bureau of Labor Statistics. Contingent and Alternative Employment Arrangements, February 2005. https://www.bls.gov/news.release/archives/conemp_07272005.pdf.

U.S. Bureau of Labor Statistics. Contingent and Alternative Employment Arrangements, May 2017. https://www.bls.gov/news.release/archives/conemp_06072018.pdf.

U.S. Census Bureau. CPS/Housing Vacancy Survey, Q4 2025. https://www.census.gov/housing/hvs/index.html.

Wall Street Journal. "Anthropic CEO Says Government Should Help Ensure AI's Economic Upside Is Shared." 2025. https://www.wsj.com/tech/ai/anthropic-ceo-says-government-should-help-ensure-ais-economic-upside-is-shared-1eab376c.

Weil, David. The Fissured Workplace: Why Work Became So Bad for So Many and What Can Be Done to Improve It. Cambridge, MA: Harvard University Press, 2014. https://www.hup.harvard.edu/books/9780674975446.

Wikipedia. "Closing Milestones of the Dow Jones Industrial Average." https://en.wikipedia.org/wiki/Closing_milestones_of_the_Dow_Jones_Industrial_Average.

Wong, Michele. "U.S. Insurance Industry's Cash and Invested Assets Rise Over 5% to Close in on $9 Trillion as of Year-End 2024." NAIC Capital Markets Bureau Special Report, May 2025. https://content.naic.org/

Appendix A: Consumption Drag and GDP Amplification

The modeled consumption contraction captures the direct effect of labor-income disruption on household spending. The direct consumption loss from labor-income disruption is estimated by applying a blended marginal propensity to consume (MPC) of 0.70 to total income lost across both fully displaced workers and gig-transitioned workers. This MPC is drawn from Johnson, Parker, and Souleles (2006), who estimate a range of 0.65–0.80 depending on household income level, with lower-income households at the higher end.[108] The 0.70 blended rate reflects the mixed income profile of the affected population across scenarios.

In addition, aggregate consumption typically falls by more than can be explained by direct income losses alone. This appendix describes two distinct methodological steps used to translate labor-income disruption into an estimate of total GDP contraction.

Step 1: From Income Loss to Full Consumption Contraction. Consumption typically declines by more than can be explained by direct income losses alone. Households that retain employment reduce spending in response to rising economic uncertainty, tighter credit conditions, and declining asset values—a precautionary and wealth-effect channel that amplifies the direct income shock. To capture this broader retrenchment, the model incorporates an additional consumption drag parameter (β), which reflects precautionary saving, reduced access to credit, and declining confidence among still-employed households. This drag is modeled as a function of overall labor-market stress—including both full displacement and partial income loss from gig transition—and is calibrated to align total consumption decline at a 10% unemployment benchmark with recession-scale outcomes observed during the GFC. The drag is modeled as a function of overall labor-market stress—the Credit Stress Rate —and is applied additively to the direct consumption loss: Total Consumption Loss = (Income Loss × MPC) + (β × Labor Stress Rate × GDP). The resulting total consumption loss as a share of GDP across scenarios is: 0.8% (Light), 3.9% (Moderate), 6.6% (High), and 9.1% (Aggressive). However, this represents only the first-order impact on GDP.

Step 2: From Consumption Contraction to GDP Contraction. In practice, declines in consumption propagate through the broader economy, generating second-order effects that amplify the overall downturn. Consumption losses propagate through the broader economy via second-order channels: firms reduce investment and hiring in response to weaker demand; rising defaults contribute to tighter credit conditions; and fiscal balances deteriorate as revenues fall and automatic stabilizers activate. Outcomes vary further depending on monetary and fiscal policy interventions, which come with their own macroeconomic implications related to currency and sovereign debt risks. To translate total consumption

[108] David S. Johnson, Jonathan A. Parker, and Nicholas S. Souleles, "Household Expenditure and the Income Tax Rebates of 2001," American Economic Review 96, no. 5 (2006): 1589–1610.

contraction into an estimate of GDP contraction, the model applies a GDP amplification multiplier of 1.23×, calibrated to GFC recession dynamics.

This 1.23× multiplier is likely conservative for the High and Aggressive scenarios. The GFC multiplier was observed under conditions of massive fiscal and monetary intervention—TARP, Federal Reserve emergency facilities, and HAMP—that partially cushioned the amplification of the initial consumption shock. Comparable policy responses may not be available or politically feasible at the scale required in those scenarios. Research on fiscal multipliers during deep recessions suggests that amplification effects scale nonlinearly with the severity of the initial shock, particularly when financial system stress is involved.[109] For the Light scenario, conversely, the multiplier likely overstates the GDP impact, since there is insufficient financial system stress to generate meaningful second-order amplification. The estimates should therefore be understood as approximate: conservative for the more severe scenarios and an upper bound for the Light scenario.

[109] Olivier J. Blanchard and Daniel Leigh, "Growth Forecast Errors and Fiscal Multipliers," IMF Working Paper No. 13/1, January 2013, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2226267; Alan J. Auerbach and Yuriy Gorodnichenko, "Measuring the Output Responses to Fiscal Policy," *American Economic Journal: Economic Policy* 4, no. 2 (2012): 1–27.

Appendix B: Detailed Methodology for Default Rate Calibration

B.1 Benchmarking Labor Market Scenario Stress Relative to the GFC

To contextualize the severity of AI-driven labor disruption, we benchmark each scenario against a GFC-equivalent stress level. The Moderate scenario is calibrated to approximate a GFC-style shock in terms of aggregate labor-market stress. The remaining scenarios can then be interpreted relative to this benchmark. Importantly, this comparison highlights a key distinction between AI-driven disruption and prior recessions. In the GFC, household stress was largely concentrated among unemployed workers, with relatively limited spillover to the broader employed population. In the scenarios modeled here, even when unemployment is similar to GFC levels (as in the Moderate case), total household stress can be slightly higher due to the addition of widespread gig-related income loss. As a result, scenarios with comparable unemployment rates may nevertheless produce different outcomes in terms of consumption, credit performance, and overall economic contraction.

The table below summarizes each scenario's position relative to the GFC benchmark. The "Credit Stress (× GFC level)" metric provides a simple way to interpret these results, incorporating both displacement and gig-transition income loss: values below 1.0 indicate less total stress than the GFC, while values above 1.0 indicate greater overall disruption. This metric provides a summary measure of labor-market-driven borrower stress relative to the GFC benchmark and serves as a common scaling variable for credit outcomes across the model. In subsequent sections, it is used to calibrate corporate default rates alongside macroeconomic contraction, providing a consistent link between household income stress and firm-level credit deterioration.

Crucially, this metric reflects the scale of household income impairment, not the severity of distress for any individual borrower. That distinction is captured separately through the composition of stress—specifically, the share attributable to full displacement versus gig-related income loss—which determines how borrower-level outcomes evolve across scenarios.

Table B.1: Credit Stress Framework and Variable Definitions

Variable	Formula	Description
Credit Stress Rate	$Displacement\_Rate + \lambda.(Gig\_Shift\_Rate \times Gig\_Wage\_Haircut)$	Blended household credit-stress measure combining full income loss from unemployment and partial income loss from gig transition, with gig effects scaled by a fragility factor (λ) to reflect higher risk from volatile earnings.
Credit Stress (× GFC level)	$\frac{Credit\_Stress\_Rate}{Credit\_Stress\_Rate_{GFC}}$	Total labor-market stress relative to a 2008-equivalent shock. Captures the overall scale of disruption, not per-borrower severity. Values above 1.0 indicate greater total stress than 2008 due to additional gig-related income loss.
Effective Displaced Share (Share of Stress from Unemployment)	$\frac{Displacement\_Rate}{Displacement\_Rate + \lambda.(Gig\_Shift\_Rate \times Gig\_Wage\_Haircut)}$	Share of total household credit stress attributable to full displacement (unemployment). Determines how close borrower outcomes are to the displaced-borrower benchmark.
Effective Gig Share (Share of Stress from Gig Income Loss)	$1 - Displacement\_Rate$	Share of total stress attributable to gig-related income loss (reduced and volatile earnings). Reflects partial rather than full income impairment.

Note: The displacement rate is the increase in unemployment relative to a benchmark unemployment level (~4.4% in 2026). To ensure consistency across calculations, the synthetic GFC credit stress measure is also anchored to this benchmark rather than the historical 2007 unemployment rate. This approach maintains comparability across scenarios by holding the baseline constant. In practice, pre-crisis unemployment levels were similar to the 2026 benchmark, so this assumption does not materially affect the results.

Table B.2: Scenario Results vs the GFC

	GFC	Light	Moderate	High	Aggressive
Unemployment Rate	10.0%	4.4%	10.0%	15.0%	20.0%
Consumption Contraction (% GDP)	~3.5%	0.9%	4.0%	6.7%	9.3%
Credit Stress Rate	5.60%	1.88%	7.35%	12.16%	16.73%
Credit Stress (× GFC level)	1	0.33	1.31	2.17	2.99
GDP Contraction (%)	4.3%	1.0%	4.9%	8.2%	11.5%
Share of Stress from Unemployment	100%	0.00%	76.19%	87.15%	93.27%
Share of Stress from Gig Income Loss	—	100.00%	23.81%	12.85%	6.73%

B.2 Default Rate Calibration for Mortgage and Household Debt

Mortgages. For mortgages, the Mortgage Bankers Association's National Delinquency Survey tracks several distinct measures of mortgage stress. Total delinquency—defined as one or more payments missed, excluding loans in active foreclosure—peaked at approximately 9.85% in Q2 2010. A narrower and more analytically precise measure, serious delinquency, captures loans that are 90 days or more past due or in the process of foreclosure. This measure peaked at 9.11% and is the standard definition of default used in the academic mortgage literature.[110] We use the serious delinquency rate of 9.11% as our GFC industry benchmark throughout, rather than the broader total delinquency figure, because it most closely corresponds to the threshold at which borrowers are no longer servicing debt obligations—the condition that generates credit losses and financial contagion.[111]

Credit Cards: The industry benchmark of 10.54% reflects the annualized charge-off rate on credit card loans at all commercial banks, which peaked in Q4 2009 (Federal Reserve Board, FRED series CORCCACBS: Charge-Off Rate on Credit Card Loans, All Commercial Banks). Note that this rate reflects an annualized charge-off rate—the rate at which balances were written off per year—rather than a stock measure of cumulative distress. As such, it is not directly comparable to the mortgage serious delinquency rate (9.11%), which measures the share of all outstanding loans in distress at a point in time. Because credit card defaults are resolved quickly (typically charged off at 180 days) while mortgage defaults accumulate in the pipeline over years, the credit card charge-off rate understates cumulative crisis-period stress relative to the mortgage benchmark. The 10.54% figure is used here as the standard crisis-period benchmark for this asset class; users should interpret cross-asset comparisons of the GFC industry peak column with this measurement difference in mind. On a cumulative basis, credit card losses over the 2008–2010 GFC window would be materially higher.

Auto Loans: The industry benchmark of approximately 2.3% reflects the charge-off rate on consumer loans at commercial banks during the crisis period, drawn from the Federal Reserve Board's Charge-Off and Delinquency Rates on Loans and Leases at Commercial Banks (H.8 release). Auto loans are included within the "Other Consumer Loans" category, which peaked at approximately 3.4–3.7% in delinquency during 2009 (30+ days past due), with charge-off rates materially lower given the secured nature of auto debt and the relative speed of collateral recovery through repossession. The 2.3% figure reflects the charge-off rate for this category at crisis peak.

[110] Including Gerardi, Herkenhoff, Ohanian, and Willen (2015), the paper anchoring our displaced-borrower calibration.
[111] Completed foreclosure rates were materially lower, peaking at approximately 4.6% of outstanding loans (MBA), reflecting the role of loan modifications, short sales, and other workout mechanisms in limiting formal foreclosure completions relative to initial defaults.

Student Loans: The 2009 repayment cohort carried a three-year cohort default rate of approximately 19%,[112] though this cumulative measure exceeds the snapshot delinquency rate used for comparability with other asset classes. Student loan defaults peaked among the 2009–2011 cohorts,[113] coinciding with the trough of the labor market recovery. The 17.6% figure used here reflects the peak share of student loan borrowers who were seriously delinquent or in default, as reported in NY Fed Liberty Street Economics research drawing on the Consumer Credit Panel.[114] This borrower-count measure exceeds the balance-weighted 90+ day delinquency rate (~11–12%) reported in the NY Fed's Quarterly Report on Household Debt and Credit, but better captures the breadth of borrower distress relevant to modeling displaced-worker default behavior.

Borrower level default benchmarks. All these rates are economy-wide averages that blend the default behavior of all borrowers, the vast majority of whom remained employed throughout the crisis. In contrast, default rates in our model are applied only to the at-risk population's share of outstanding debt. Rather than applying a single economy-wide stress multiplier, we calibrate default rates using a borrower-level anchor approach that explicitly distinguishes between different types of labor-market impairment. The GFC experience provides two empirical anchor points for borrower behavior. In their Federal Reserve Bank of Boston Working Paper, Gerardi, Herkenhoff, Ohanian, and Willen (2015) found that unemployed borrowers were approximately three times as likely to default on mortgages as employed borrowers.[115] Using this finding, we decompose all observed economy-wide default rates into:

- an employed-borrower benchmark (r), and
- a displaced-borrower benchmark (3r)

Note that the 3× multiplier applied to displaced borrowers is calibrated from mortgage default behavior (Gerardi et al., 2015), but we apply this 3x multiplier uniformly across all debt categories (credit cards, auto loans, student debt) as a simplifying assumption. While empirical sensitivities may differ by asset class, applying a common multiplier provides a consistent framework for translating labor-market disruption into borrower-level distress.[116]

---

[112] Meta Brown, Andrew F. Haughwout, Donghoon Lee, Joelle Scally, and Wilbert van der Klaauw, "Looking at Student Loan Defaults through a Larger Window," *Liberty Street Economics* (blog), Federal Reserve Bank of New York, February 19, 2015, https://libertystreeteconomics.newyorkfed.org/2015/02/looking_at_student_loan_defaults_through_a_larger_window/.

[113] Andrew F. Haughwout, Donghoon Lee, Joelle Scally, and Wilbert van der Klaauw, "Are Student Loan Defaults Cyclical? It Depends," *Liberty Street Economics* (blog), Federal Reserve Bank of New York, November 22, 2017, https://libertystreeteconomics.newyorkfed.org/2017/11/are-student-loan-defaults-cyclical-it-depends/.

[114] Andrew Haughwout, Donghoon Lee, Daniel Mangrum, Joelle Scally, and Wilbert van der Klaauw, "Student Loan Balance and Repayment Trends Since the Pandemic Disruption," *Liberty Street Economics* (blog), Federal Reserve Bank of New York, March 2025, https://libertystreeteconomics.newyorkfed.org/2025/03/student-loan-balance-and-repayment-trends-since-the-pandemic-disruption/.

[115] The Gerardi et al. finding is based on Panel Study of Income Dynamics (PSID) data from the 2008–2010 period and controls for the level of negative equity.

[116] Our uniform application of 3x is a simplification that produces moderate estimates across all categories and maintains transparency. A more granular model could assign differentiated multipliers by debt type; we note this as an area for future refinement. In practice, default hierarchies differ across debt types. The payment priority literature (e.g., TransUnion and Experian consumer credit studies) consistently shows that during periods of financial stress, consumers prioritize mortgage and auto loan payments — which are secured by essential assets — over unsecured obligations like credit cards, and over student loans where federal income-driven repayment plans provide a buffer. This could suggest the true displaced-population multiplier might be higher than 3x for credit cards and lower than 3x for auto loans.

Table B.3: Borrower-Level Default Benchmarks vs. GFC Industry Averages

Asset Class	Employed Borrower (r)	Displaced Borrower (3r)	GFC Industry Peak	Source
Mortgages	7.59%	22.78%	9.1%	MBA; Statista
Credit Cards	8.75%	26.25%	10.5%	FRED (CORCCACBS)
Auto Loans	1.88%	5.63%	2.3%	Federal Reserve (charge-off data)
Student Loans	14.67%	44.00%	17.6%	NY Fed; Liberty Street Economics

For each asset class, default rates for displaced gig workers and fully displaced unemployed workers are calibrated with two scenarios. A more conservative scenario uses an anchor point (“low”) directly based on the GFC default benchmarks. A more aggressive scenario uses an anchor point (“high”) that is based on the GFC default benchmarks but is adjusted to reflect the specific structure of AI-driven disruption for both gig workers and unemployed workers.

Default rates for each scenario are then determined by blending between these anchors based on the composition of labor-market stress. Scenarios with more displacement move closer to the displaced-borrower benchmark, while scenarios dominated by gig-style income loss remain closer to the gig-stressed anchor.[117]

The high anchor points are calibrated as follows. First, we introduce a gig-stress adjustment. Workers who are not fully displaced but transition into gig or contract work retain income, but at reduced levels and with substantially higher volatility. To reflect this, we apply a modest uplift to the GFC employed-borrower benchmark (r), producing a gig-stressed anchor. This captures the fact that these workers are less risky than fully displaced borrowers, but more vulnerable than stable employed households. Second, we allow for the possibility that displacement under AI may be more severe than in the GFC. The GFC recession was cyclical: jobs returned without extended reskilling periods required, and unemployment spells were finite. In contrast, AI-driven displacement may eliminate roles permanently across multiple sectors, require investments of time and monetary resources into reskilling, extend unemployment durations, and lead to persistent wage downgrades upon re-employment. To reflect this, the high-end calibration applies an additional uplift to the GFC displaced-borrower benchmark (3r), allowing default behavior to exceed GFC levels in more extreme scenarios.

Overall, this approach separates two key dimensions of risk 1) the scale of stress (how many households are affected), and 2) the severity of stress (how impaired the average borrower is), allowing both to evolve realistically across scenarios. The table below presents the scenario-specific distress rates positioned relative to these benchmarks.

[117] In the Light scenario, the at-risk share consists entirely of gig-transitioned workers. In the Moderate through Aggressive scenarios, the share is dominated by displaced workers, with gig-transitioned workers contributing a declining additional component. The partially substitutive relationship between displacement and gig reclassification (§1.3) concentrates disruption in outright job loss at higher severity levels.

Table B.4: Calibrated Borrower-Level Default Rates vs. GFC Displaced Benchmark

Asset Class	GFC Displaced (3r)	Light	Moderate	High	Aggressive
Mortgages	22.78%	7.59–8.73%	19.16–19.43%	20.82–24.94%	21.75–30.33%
Credit Cards	26.25%	8.75–10.06%	22.08–22.40%	24.00–28.75%	25.07–34.95%
Auto Loans	5.63%	1.88–2.16%	4.73–4.80%	5.14–6.16%	5.37–7.49%
Student Loans	25.00%	8.33–9.58%	18.24–21.33%	24.93–27.38%	31.61–33.29%

It is important to consider that the lower pay, higher volatility, and loss of employer-provided safety nets associated with gig-work can raise default risk even in the absence of headline unemployment. JPMorgan Chase Institute research found that the majority of lower-income and younger workers experience average month-to-month income changes exceeding 30 percent, with median income volatility across all families running at approximately 36 percent (Farrell and Greig, 2016; Farrell, Greig, and Yu, 2019).[118] This level of variability makes fixed debt obligations—mortgages, auto loans, student loan payments—difficult to service even when average income appears sufficient on paper. The loss of employer-provided safety nets compounds this effect: gig workers lack employer-sponsored health insurance, have no access to employer retirement matching, and cannot draw on employer-funded short-term disability or severance in the event of income disruption.

B.3 Calibration Methodology for Corporate Default Rates

The quantitative estimates use economy-wide blended rates for IG and HY bonds because the corporate bond market is interconnected—systemic defaults in high-exposure sectors trigger credit tightening, counterparty risk, and risk repricing that affect the entire market. The GFC demonstrated this contagion: what began as a housing-sector problem ultimately produced corporate defaults across all industries. At the peak of the GFC, IG default rates reached approximately 0.4% and HY default rates approximately 10.7%, implying a blended corporate default rate of roughly 3.6% (S&P Global, 2009 Annual Default Study).

[118] The income volatility figures cited here draw on two JPMorgan Chase Institute studies that analyzed anonymized banking transaction data from millions of Chase customers — one of the largest administrative datasets on household income dynamics available. The 2016 report, "Paychecks, Paydays, and the Online Platform Economy" (Farrell and Greig, 2016), analyzed 1.9 billion inflow transactions across a sample of 1 million individuals and a separate sample of 260,000 platform economy participants. It found that the vast majority of workers aged 18–24, individuals in the bottom income quintile, and those living in the western United States experienced average month-to-month income changes exceeding 30 percent. For workers broadly, 61 percent experienced idiosyncratic fluctuations in labor income that produced absolute monthly changes of approximately 27 percent. The 2019 follow-up, "Weathering Volatility 2.0: A Monthly Stress Test to Guide Savings" (Farrell, Greig, and Yu, 2019), reported a median coefficient of variation for total income of approximately 36 percent month-to-month, and found that 65 percent of families lacked sufficient liquid savings to weather a simultaneous income dip and expenditure spike. These findings describe income volatility across all workers, not platform workers exclusively. For platform economy participants specifically, the 2016 study found that labor platform earnings represented approximately 33 percent of total monthly income in months when platform income was earned, with reliance highest among low-income workers (over 25 percent of annual income for the bottom three income quintiles). The broader income volatility findings are relevant to our analysis because they demonstrate that significant volatility is already a feature of the labor market for lower-income and younger workers — precisely the populations most likely to be pushed into gig arrangements by AI-driven reclassification. The transition from salaried employment to contract work would compound existing volatility by removing the stabilizing features of regular paychecks, employer-provided benefits, and paid leave. (Sources: Farrell, D. and Greig, F. (2016), "Paychecks, Paydays, and the Online Platform Economy: Big Data on Income Volatility," JPMorgan Chase Institute; Farrell, D., Greig, F., and Yu, C. (2019), "Weathering Volatility 2.0: A Monthly Stress Test to Guide Savings," JPMorgan Chase Institute.)

Corporate default rates are calibrated as a function of both labor-market-driven income stress and macroeconomic contraction, consistent with standard reduced-form credit risk frameworks. Empirical and structural models used by rating agencies and regulators typically relate default rates to a combination of output dynamics, labor-market conditions, macro and financial variables, reflecting the joint role of borrower cash flow deterioration and broader economic conditions in driving credit outcomes.[119] Structural models of credit risk similarly imply that default probabilities rise as firm asset values decline with falling revenues and economic activity.[120] Default risk increases most sharply when income stress and macroeconomic contraction occur simultaneously.

In our framework, these two channels are represented by (1) labor-market income stress, captured by the Credit_Stress_vs_GFC metric; this measure extends conventional unemployment-based indicators by incorporating both full displacement and gig-transition income loss, weighted by borrower fragility, thereby reflecting the effective erosion of debt-service capacity across households rather than headline unemployment alone; and (2) macroeconomic contraction, captured by scenario-specific GDP decline. This reflects the broader environment in which firms operate, including aggregate demand reduction, tightening credit conditions, and indirect effects such as precautionary savings and wealth-driven consumption changes.

Corporate Stress Factor. To operationalize these dynamics in a scenario-based framework, a Corporate Stress Factor (CSF) is constructed as a weighted combination of labor-market stress and GDP contraction, each expressed relative to the GFC benchmark.

Mapping to Default Rates. IG and HY default rates are derived by mapping the CSF to default probabilities using a low–high framework anchored to current conditions and the GFC peak. In the **low case,** default rates scale linearly from current levels to the GFC benchmark and continue proportionally above it, reflecting a conservative scenario with limited nonlinear amplification. In the **high case**, default rates follow the same path up to the GFC benchmark but increase more rapidly beyond it, capturing the potential for nonlinear deterioration in credit quality under more severe stress. This effect is modest for investment-grade issuers but more pronounced for speculative-grade issuers, reflecting differences in leverage, operating risk, and sensitivity to revenue declines. This asymmetric scaling is consistent with historical experience, including the GFC, in which HY default rates increased multiple times more than IG rates.[121]

---

[119] The Federal Reserve's supervisory stress testing framework models default risk and credit losses as a function of macroeconomic variables including GDP, unemployment, and financial conditions, with default probabilities embedded within these loss projections. Also see Moody's Analytics, Credit Cycle Indicators and Default Modeling Methodologies; S&P Global, Annual Global Corporate Default and Rating Transition Studies (various years). Both frameworks model default rates as functions of macroeconomic and financial variables.

[120] Robert C. Merton (1974), "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance*. Structural model linking default risk to firm asset values and economic conditions.

[121] Standard & Poor's Ratings Services. (2010). *Default, Transition, and Recovery: 2009 Annual Global Corporate Default Study and Rating Transitions*. March 17, 2010.

Interpretation in the AI Context. A key feature of this framework is that it incorporates AI-specific labor-market dynamics directly into the credit stress measure. Because Credit_Stress_vs_GFC includes gig-transition income loss and wage compression, scenarios with similar unemployment rates to the GFC may nonetheless generate higher effective stress. GDP contraction captures the additional macroeconomic amplification arising from reduced consumption, tighter credit conditions, and wealth effects. The combination of these channels allows default rates in severe scenarios to exceed GFC levels without relying on purely mechanical scaling, reflecting the possibility that AI-driven disruption is more structural and persistent than prior cyclical downturns.

Table B.5: Mapping Corporate Stress to Default Rates

Variable	Formula	Description
Corporate Stress Factor (CSF)	$CSF = (1-w).\frac{Credit\_Stress\_Rate}{Credit\_Stress\_Rate_{GFC}} + w.\frac{GDP\_contraction}{GDP\_contraction_{GFC}}$	Weighted measure of overall credit stress relative to the GFC benchmark, combining labor-market-driven income stress and GDP contraction. Reflects both borrower-level deterioration in debt-service capacity and the broader macroeconomic environment affecting corporate revenues and credit conditions. In the baseline calibration, $w = 0.3$, reflecting the primacy of income-driven borrower stress while incorporating the amplifying effects of broader economic deterioration.
IG Default Rate	$D^{IG}_{Low} = D^{IG}_{current} + (D^{IG}_{GFC} - D^{IG}_{current}).CSF$ $D^{IG}_{High} = \{D^{IG}_{current} + (D^{IG}_{GFC} - D^{IG}_{current}).CSF, CSF \leq 1\ D^{IG}_{GFC} + \beta_{IG}.(CSF-1), CSF > 1$	Low: Linear scaling from current conditions to the GFC peak based on the CSF, with no additional acceleration beyond the GFC. Reflects a conservative scenario in which IG defaults remain relatively stable even under severe stress. High: Default rates increase linearly from current conditions to the GFC peak as stress approaches crisis levels. Above the GFC benchmark, defaults continue to rise, but at a moderate rate reflecting the relative resilience of IG issuers.
HY Default Rate	$D^{HY}_{Low} = D^{HY}_{current} + (D^{HY}_{GFC} - D^{HY}_{current}).CSF$ $D^{HY}_{High} = \{D^{HY}_{current} + (D^{HY}_{GFC} - D^{HY}_{current}).CSF, CSF \leq 1\ D^{HY}_{GFC} + \beta_{SG}.(CSF-1), CSF > 1$	Low: Linear scaling from current or long-run default rates to the GFC peak, without additional nonlinear effects. Represents a scenario in which HY defaults increase proportionally with stress but do not exhibit severe amplification. High: Default rates increase from current or long-run levels to the GFC peak under moderate stress. Beyond GFC conditions, defaults rise more sharply due to higher leverage and operating risk, producing a nonlinear response.
Key Properties	• CSF = 1: corresponds to GFC-equivalent stress • CSF $\leq$ 1: interpolation between current conditions and 2008 • CSF > 1: stress exceeds GFC, with continued increases in default $\beta_{HY} > \beta_{IG}$: speculative-grade defaults scale more aggressively	The parameters β_{IG} and β_{HY} govern the increase in default rates above the GFC stress benchmark. They are calibrated to align with historical default behavior and the scenario ranges presented, with HY defaults scaling more rapidly than IG defaults to reflect higher leverage and operating sensitivity. We use β_{IG} = 0.45% and β_{IG} = 7.5%

As with past sections of this discussion paper, we acknowledge additional feedback loops and second- and third-order effects—behavioral responses, international contagion, credit market freezes—that our framework does not fully capture, or that would require different β_{IG} and β_{HY} parameters. The figures should therefore be understood as a structured starting point for quantifying corporate credit risk, not a complete accounting of it.

B.4 Calibration Methodology for Corporate Mark-to-Market (MTM)

The calibration framework mirrors the structure used for corporate default rates:

Table B.6: Corporate Bond MTM Calibration Framework

Variable	Formula	Description
Corporate MTM Loss (Low)	$MTM_{Low}^{IG} = min(MTM_{GFC}^{IG} \times CSF, MTM_{GFC}^{IG})$ $MTM_{Low}^{HY} = min(MTM_{GFC}^{HY} \times CSF, MTM_{GFC}^{HY})$	Low case: mark-to-market losses scale linearly with the CSF from zero to the GFC benchmark, but do not exceed the GFC peak. At CSF = 0 (no stress), losses are zero; at CSF = 1 (GFC-equivalent stress), losses reach the full benchmark of 19.2% (IG) and 34.38% (HY). At CSF > 1, losses stay at those GFC peaks. This represents a conservative scenario in which credit spread widening reaches but does not overshoot historical crisis levels, even under severe stress—reflecting the possibility that policy intervention, market structure changes since the GFC, or flight-to-quality dynamics in investment-grade credit limit spread overshooting.
Corporate MTM Loss (High)	$MTM_{High}^{IG} = \begin{cases} MTM_{GFC}^{IG} \times CSF, CSF \leq 1 \\ MTM_{GFC}^{IG} + \beta_{spread}^{IG} \times (CSF - 1), CSF > 1 \end{cases}$ $MTM_{High}^{HY} = \begin{cases} MTM_{GFC}^{HY} \times CSF, CSF \leq 1 \\ MTM_{GFC}^{HY} + \beta_{spread}^{HY} \times (CSF - 1), CSF > 1 \end{cases}$	High case: mark-to-market losses follow the same linear path up to the GFC benchmark. Above CSF = 1, losses increase more rapidly, reflecting the nonlinear liquidity withdrawal that occurs when credit markets seize—the GFC experience showed spreads gapping wider than fundamentals alone would predict, driven by forced selling, counterparty fear, and the disappearance of market-making capacity.
Parameters	***CSF = 1:*** corresponds to 2008-equivalent spread widening (~600bps IG, ~20% MTM). ***CSF ≤ 1:*** linear interpolation between current conditions and 2008. ***CSF > 1:*** continued spread widening, with potential nonlinear amplification in the high case. β_{spread} = 6%	

B.5 Equity Decline Methodology

Equity market declines are calibrated by decomposing the GFC into an earnings channel and a valuation channel and scaling each relative to scenario severity. Earnings declines scale with consumption contraction relative to the GFC benchmark, while valuation compression scales with overall economic stress relative to the GFC. Low and high estimates reflect uncertainty in the degree of amplification across both channels, particularly in severe scenarios where operating leverage and valuation effects intensify.

Table B.7: Equity Market Decline Calibration Framework

Component	Formula	Explanation
Earnings Decline Consumption → Earnings	$E_{Low} = E_{GFC} \cdot \left(\frac{C}{C_{GFC}}\right)^{\propto_{Low}}$	Earnings decline scales with consumption contraction relative to the GFC benchmark. The low case assumes limited operating leverage. E_{Low}= Earnings decline (low) E_{GFC} = Earnings decline observed in the GFC benchmark C = Scenario consumption contraction (low and high). C_{GFC} =Consumption contraction in the GFC benchmark $\propto_{Low}$ = Earnings sensitivity parameter (low)
	$E_{High} = E_{GFC} \cdot \left(\frac{C}{C_{GFC}}\right)^{\propto_{High}}$	The high case allows greater amplification of earnings declines as revenues fall. E_{High}= Earnings decline (high) E_{GFC} = Earnings decline observed in the GFC benchmark C = Scenario consumption contraction (low and high). C_{GFC} =Consumption contraction in the GFC benchmark $\propto_{High}$= Earnings sensitivity parameter (high)
Valuation Compression Stress → Multiples	$M_{Low} = M_{GFC} \times CSF^{\beta_{Low}}$	Valuation multiples compress as overall economic stress rises relative to the GFC. The low case assumes more limited multiple compression. M_{Low} = Implied valuation compression (low) M_{GFC} =Implied valuation compression in the GFC benchmark CSF = the weighted measure of overall credit stress relative to the GFC benchmark, combining labor-market-driven income stress and GDP contraction. β_{Low} = Valuation multiple sensitivity parameter (low)
	$M_{High} = M_{GFC} \times CSF^{\beta_{High}}$	The high case reflects stronger compression as uncertainty and risk premia increase. M_{High} = Implied valuation compression (high) M_{GFC} =Implied valuation compression in the GFC benchmark CSF = the weighted measure of overall credit stress relative to the GFC benchmark, combining labor-market-driven income stress and GDP contraction. β_{High}= Valuation multiple sensitivity parameter (high)
Equity Market Decline Earnings × Multiple	$D_{Low} = 1 - (1 - E_{Low})(1 - M_{Low})$	Total equity decline reflects the combined effect of earnings contraction and valuation compression, which compound multiplicatively.
	$D_{High} = 1 - \left(1 - E_{High}\right)\left(1 - M_{High}\right)$	The high case captures greater nonlinear amplification across both channels under severe stress.
Parameters	E_{GFC} = 45% C_{GFC}= 3.5% $M_{GFC} = \frac{S\&P\_500\_decline}{E_{GFC}} \approx 21\%$ $\propto_{Low}$ is set above proportional in the Light scenario to maintain sensitivity below the GFC benchmark and reduced in more severe scenarios to limit over-amplification at higher stress levels. $\propto_{High}$ is set below proportional in the Light scenario to preserve low–high ordering under mild shocks, and modestly higher in more severe scenarios to allow nonlinear earnings deterioration.	Earnings responses (elasticity) reflect uncertainty in operating leverage, with declines scaling nonlinearly with demand and allowing for greater amplification in more severe scenarios.

Component	Formula	Explanation
	β_{Low} is set below 1 in the Light scenario to reflect muted multiple compression at low stress, and near 1 in more severe scenarios (valuations adjusts more proportionally to macro conditions). β_{Low} is set below 1 in the Light scenario to avoid early over-correction, and above 1 in more severe scenarios to capture nonlinear multiple compression driven by financial stress.	

Appendix C: Detailed Methodology for Portfolio Impacts

C.1 Retirement Assets

Table C.1 consolidates equity, fixed-income, and residual allocation estimates across the $49.1 trillion US retirement asset base.[122] We estimate that approximately 52.8% of total retirement assets, or roughly $25.9 trillion, is allocated to equities, and approximately 23.1% of total retirement assets, or roughly $11.3 trillion, is allocated to fixed income broadly defined—encompassing Treasury securities, corporate and municipal bonds, agency debt, bond mutual funds, and the fixed-income portions of target date and balanced funds. The remaining approximately 24.1% of retirement assets is computed as a residual consisting of cash and cash equivalents, insurance contracts, alternative investments (principally in state and local pension portfolios), and other miscellaneous assets.

Table C.1: Estimated Asset Class Allocation Across US Retirement Assets, Q4 2025

Segment	Assets ($T)	Equity %	Equity ($T)	Fixed Income %	Fixed Income ($T)	Other / Residual %	Other ($T)
IRAs[123]	19.20	55.0%	10.56	17.0%	3.26	28.0%	5.38
401(k) Plans[124]	10.10	74.6%	7.53	5.3%	0.54	20.1%	2.03
Other DC Plans (403b / 457 / TSP / other)[125]	4.10	74.6%	3.06	5.3%	0.22	20.1%	0.82
Government DB Plans—TOTAL	10.00	30.4%	3.04	46.0%	4.60	23.6%	2.36
↳ State & Local DB[126]	6.85	44.4%	3.04	21.1%	1.45	34.5%	2.36
↳ Federal Civilian DB (CSRDF)[127]	1.20	0.0%	0.00	100.0%	1.20	0.0%	0.00

[122] All segment asset totals from Investment Company Institute (ICI), *Quarterly Retirement Market Data: Fourth Quarter 2025* (March 26, 2026), https://www.ici.org/statistical-report/ret_25_q4. Other / residual encompasses cash and cash equivalents, stable value funds, alternatives, real assets, and other miscellaneous holdings. Implied totals are computed weighted averages, not directly reported aggregates. Additional empirical anchors for fixed income from the Federal Reserve Z.1 (January 2026 release): $1.8T in debt securities held by private pension funds (FRED series PPFDSA, https://fred.stlouisfed.org/series/PPFDSA) and $1.1T in Treasury securities across pension funds (FRED series BOGZ1FL593061105Q, https://fred.stlouisfed.org/series/BOGZ1FL593061105Q).

[123] Investment Company Institute, "Ten Important Facts about IRAs," July 2024, https://www.ici.org/system/files/2022-07/ten-facts-iras.pdf. Equity allocation reflects equity funds (equity mutual funds, equity closed-end funds, and equity ETFs) as a share of IRA mutual fund assets. Fixed income allocation reflects bond funds on the same basis. Neither estimate includes non-target balanced funds, which represent approximately 13% of IRA mutual fund assets and invest in a mix of equities and fixed-income securities; the allocation of these funds between asset classes is not available and is excluded from both figures.

[124] Investment Company Institute, "The BrightScope/ICI Defined Contribution Plan Profile: A Close Look at 401(k) Plans, 2023," *ICI Research Perspective* 32, no. 2 (April 2026), https://www.ici.org/system/files/2026-04/per32-02.pdf. Equity allocation includes equity funds, company stock, and the equity portion of balanced funds. Fixed income allocation reflects bond funds only and excludes stable value contracts, guaranteed investment contracts (GICs), and the fixed income portion of balanced funds, which are reflected in the residual.

[125] Allocation for other DC plans (403(b), 457, TSP, and other private plans) is assumed equal to 401(k) plans. Further analysis would be needed to refine this analysis.

[126] Federal Reserve Board and National Association of State Retirement Administrators, "Public Pension Assets," accessed May 2026, https://www.nasra.org/content.asp?admin=Y&contentid=200. State and local DB plan assets of $6.85 trillion reflect the Federal Reserve Financial Accounts of the United States (Z.1) as of Q4 2025. Equity allocation of 44.4% and fixed income allocation of 21.1% reflect the average asset allocation reported for state and local public pension funds for fiscal year 2024, weighted by plan size. National Association of State Retirement Administrators, "Public Fund Survey: Summary of Findings for FY 2024," 2025, https://www.nasra.org/files/Public%20Fund%20Survey/FY24/Public%20Fund%20Survey%20Summary%20of%20Findings%20for%20FY%2024.pdf.

[127] U.S. Office of Personnel Management, "FY 2025 Congressional Budget Justification and Annual Performance Plan: Earned Benefits Trust Funds," 2024, https://www.opm.gov/about-us/fy-2025-congressional-budget-justification-and-annual-performance-plan/earned-benefits-trust-funds/. The Civil Service Retirement and Disability Fund (CSRDF) is invested exclusively in special-issue U.S. Treasury securities by statute; see 5 U.S.C. §8348, https://www.law.cornell.edu/uscode/text/5/8348.

Segment	Assets ($T)	Equity %	Equity ($T)	Fixed Income %	Fixed Income ($T)	Other / Residual %	Other ($T)
↳ Military + Other Federal[128]	1.95	0.0%	0.00	100.0%	1.95	0.0%	0.00
Private-Sector DB Plans[129]	3.10	23.7%	0.73	53.5%	1.66	22.8%	0.71
Annuity Reserves Outside Retirement Accounts—TOTAL	2.60	38.2%	0.99	40.9%	1.06	20.9%	0.55
↳ Variable Annuity (VA) Separate Accounts[130]	1.40	69.1%	0.97	18.1%	0.25	12.8%	0.18
↳ Fixed / Indexed Annuity (General Account)[131]	1.20	2.2%	0.03	67.6%	0.81	30.2%	0.36
Total	**49.10**	**52.8% (implied)**	**25.92**	**23.1% (implied)**	**11.34**	**24.1%**	**11.84**

Within the $11.3 trillion fixed-income allocation, on a weighted-average basis across all retirement segments, we estimate approximately 72% of retirement fixed-income assets are allocated to government, agency, and agency MBS; approximately 24.5% to IG corporate bonds; and approximately 3.5% to HY corporate bonds.[132] These sectoral estimates are approximations derived from benchmark compositions and industry survey literature rather than directly observed allocations, and carry meaningful uncertainty particularly for IRA and state and local pension fixed income, where product-level data on within-fixed-income composition is not publicly available in disaggregated form.[133]

---

[128] U.S. Department of Defense, Office of the Actuary, "DoD Statistical Report on the Military Retirement System, FY 2024," 2024, https://actuary.defense.gov/Portals/15/Documents/statbook24.pdf. Military retirement fund assets are invested exclusively in special-issue Treasury securities by law; see 10 U.S.C. §1467, https://uscode.house.gov/view.xhtml?req=granuleid:USC-prelim-title10-section1467&num=0&edition=prelim. The military and other federal DB asset figure of $1.95 trillion is computed as a residual from total government DB assets ($10.0T) less state and local DB assets ($6.85T) and federal civilian DB assets ($1.2T).

[129] Milliman, "2024 Corporate Pension Funding Study," April 2024, https://www.milliman.com/en/insight/2024-corporate-pension-funding-study. Equity allocation of 23.7% and fixed income allocation of 53.5% reflect the average asset allocation reported for the Milliman 100 largest U.S. corporate defined benefit pension plans at fiscal year-end 2023.

[130] Federal Reserve Board, "Financial Accounts of the United States, Z.1: L.116.s Life Insurance Companies: Separate Accounts, Q4 2023," June 7, 2024, https://www.federalreserve.gov/releases/z1/20240607/html/l116s.htm. Equity allocation of 69.1% is computed as (corporate equities + variable annuity mutual fund shares) / total financial assets = ($567.5B + $1,526.2B) / $3,027.7B. Fixed income allocation of 18.1% is computed as debt securities / total financial assets = $549.1B / $3,027.7B, using the debt securities line only and excluding mortgage loans. Both figures use the most recent year-end data available at the time of calculation. See methodology note for caveats regarding the scope of the Z.1 denominator relative to the ICI VA mutual fund assets figure.

[131] National Association of Insurance Commissioners, "U.S. Life and A&H Insurance Industry Analysis Report: 2024 Annual Results," 2025, Table 7 — Invested Assets, https://content.naic.org/sites/default/files/2024-annual-life-industry-commentary.pdf. Equity allocation of 2.2% reflects common stock (1.9%) plus preferred stock (0.3%) as a share of total invested assets for the life and A&H industry. Fixed income allocation of 67.6% reflects bonds as a share of total invested assets. These figures are applied as a proxy for the fixed and indexed annuity general account given the absence of a publicly available product-specific source; see methodology note for full discussion of the proxy rationale and limitations. Fixed and indexed annuity assets of $1.2 trillion are computed as a residual from total annuity reserves outside retirement accounts ($2.6T) less variable annuity separate account assets ($1.4T).

[132] As a percentage of total corporate bonds, this represents an allocation of approximately 87% IG and 13% HY.

[133] No publicly available source reports the within-fixed-income sectoral breakdown — government/agency/MBS, investment-grade corporate, and high yield — for U.S. retirement assets at the segment level. The estimates in this table are therefore approximations derived from benchmark compositions, plan-level survey data, and industry literature, organized by the investment mandate governing each segment.
Federal government DB plans (CSRDF and military). The Civil Service Retirement and Disability Fund and military retirement funds are invested exclusively in special-issue U.S. Treasury securities by statute (5 U.S.C. §8348 and 10 U.S.C. §1467 respectively). No estimation is required; the 100% government allocation is a legal constraint.
DC plans (401(k) and other DC). Fixed-income exposure in defined-contribution plans is predominantly implemented through core bond and target-date fund strategies benchmarked to the Bloomberg U.S. Aggregate Bond Index. The Aggregate Index is approximately 70% government, agency, and agency MBS; 25% investment-grade corporate; and 5% other. The DC allocation assumption directly approximates this benchmark composition.
IRAs. IRA fixed-income assets are held through a combination of bond mutual funds, balanced funds, and self-directed brokerage accounts, with somewhat greater use of active management and credit-oriented strategies than employer-sponsored DC plans. The allocation assumption modestly increases investment-grade corporate exposure to 30% relative to the DC/Aggregate benchmark while holding government/agency/MBS and high yield constant.
State and local DB plans. Unlike corporate DB plans, public pension funds discount liabilities using an assumed rate of return rather than corporate bond yields, and therefore have no LDI mandate to concentrate in corporate bonds. Their fixed-income allocation functions as a

Table C.2: Estimated sectoral composition of retirement fixed-income allocations

Investor type	FI assets ($T)	Govt / Agency / MBS	IG Corporate	High yield / other
IRAs	3.26	65%	30% (85.7%)	5% (14.3%)
401(k) / DC plans	0.54	70%	25% (83.3%)	5% (16.7%)
Other DC (403b / 457 / TSP)	0.22	70%	25% (83.3%)	5% (16.7%)
Government DB—total	4.60	90.6%	7.9% (83.3%)	1.6% (16.7%)
↳ State & local DB	1.45	70%	25% (83.3%)	5% (16.7%)
↳ Federal civilian DB (CSRDF)	1.20	100%	—	—
↳ Military + other federal	1.95	100%	—	—
Private-sector DB plans	1.66	35%	60% (92.3%)	5% (7.7%)
Weighted average	10.27	72.0%	24.6% (87.6%)	3.5% (12.4%)
Bloomberg US Aggregate (reference)	—	*~70%*	*~25%*	*~5%*

Allocation assumptions by investor type · FI assets in $T · parentheses show % of total corporate credit. All allocation assumptions are approximations derived from benchmark compositions and industry survey literature. Federal government DB allocations (CSRDF and military) are 100% special-issue Treasury securities by statute. Annuity reserves ($1.06T) excluded—sectoral composition not separately estimated (further analysis would be required).

All sectoral allocations, except those mandated by statute, are estimates. The IRA and state and local DB figures in particular carry meaningful uncertainty, as product-level data on within-fixed-income composition for these segments is not publicly available in disaggregated form. Annuity reserves ($1.06T in fixed-income assets) are excluded from the sectoral breakdown, as no reliable public source allows estimation of the government/corporate/high-yield split within variable annuity bond subaccounts or life insurer general account bond portfolios at this level of granularity. The weighted-average figures should therefore be interpreted as approximations anchored to the Bloomberg US Aggregate as a structural reference rather than as precisely observed allocations.

Government bond holdings in retirement portfolios are subject to mark-to-market losses from rising long-term interest rates. Unlike a typical recession—where long-term rates tend to fall via flight-to-quality dynamics—our scenarios assume that fiscal stress dominates: mass displacement simultaneously drives large-scale safety-net expenditures and collapses tax revenue, producing deficit expansion severe enough to widen term premia on sovereign debt. We estimate losses using a duration-based approximation, assuming an average portfolio duration of approximately six years, where each 100 basis point rate increase reduces market value by roughly 5.5–6%, with positive convexity moderating losses at larger rate

total-return diversifier and is typically benchmarked to the Bloomberg U.S. Aggregate. The allocation assumption therefore approximates Aggregate Index composition.

Private-sector DB plans. Corporate defined benefit pension plans predominantly use liability-driven investment strategies in which the fixed-income portfolio is designed to hedge liabilities discounted at high-quality corporate bond yields under U.S. accounting rules (ASC 715). This creates a structural incentive to hold long-duration investment-grade corporate bonds rather than Treasury-heavy aggregate strategies. The allocation assumption of 60% investment-grade corporate and 35% government/agency/MBS reflects the credit-oriented character of LDI benchmarks as described in J.P. Morgan Asset Management, "A New Chapter for Pension Fixed Income" (April 2025). These figures are approximations consistent with industry LDI literature and are not directly observed from plan-level data.

moves. We anchor the calibration at the Moderate scenario (~1.3× GFC credit stress), centering on an implied rate increase of approximately 100 basis points, and scale the remaining scenarios proportionally at roughly 75 basis points per 1× credit stress multiple. For partial reference, nominal gilt yields across the medium and long maturity spectrum rose by more than 100 basis points in a matter of days following the September 2022 mini-budget announcement—an unprecedented move in recent UK economic history driven by sudden loss of confidence in fiscal sustainability.[134] We note that the transmission from AI-driven labor displacement to sovereign borrowing costs lacks a dedicated empirical literature, and this channel should be treated as indicative pending further research.

Table C.3: Portfolio Government Bond Losses—Interest Rate Risk

Scenario	Credit Stress (×GFC)	Implied Rate Increase (bp)	Duration Sensitivity	MTM Loss (%)
Light	0.33×	25–50bp	~5.5–6% per 100bp	1–3%
Moderate	1.31×	75–125bp	~5.5–6% per 100bp	4–7%
High	2.17×	125–200bp	~5.5–6% per 100bp	7–12%
Aggressive	2.99×	175–275bp	~5.5–6% per 100bp	10–14%

Note that equity allocations reflect publicly traded equities only—equity mutual funds, equity ETFs, equity closed-end funds, company stock, and the equity portions of target-date and balanced funds—and do not include private equity or other alternative investments.[135]

Table C.4: Retirement Portfolio Equity Losses ($25.9T outstanding)

Scenario	Equity Decline (%)	Loss ($T)
Light	19.7–25.0%	$5.1–6.5T
Moderate	59.9–60.9%	$15.6–15.8T
High	71.3–83.6%	$18.6–21.8T
Aggressive	83.1–95.6%	$21.6–24.9T

Fixed income losses are modeled through three distinct sub-channels, applied to the approximately $11.3 trillion in bonds held within retirement portfolios: corporate bond defaults, corporate bond mark-to-market losses, and government bond mark-to-market losses, each calibrated independently due to the fact that they are driven by different risk factors (credit risk, spread risk, and interest rate risk respectively)

[134] Gabor Pinter, "An Anatomy of the 2022 Gilt Market Crisis," Bank of England Staff Working Paper No. 1,019 (March 2023) https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2023/an-anatomy-of-the-2022-gilt-market-crisis.pdf.

[135] Private equity (PE) exposure in defined contribution plans is currently negligible, although legislative developments are expected to change this. Currently the primary pathway for PE in DC plans is a small allocation within target-date funds rather than standalone investment options. PE exposure is more meaningful in government DB plans, where alternatives (including PE, real estate funds, and hedge funds) represent approximately 31.7% of assets (Equable Institute, State of Pensions 2025); this exposure is captured in the ~20% residual allocation category rather than the equity figures reported here. To the extent PE valuations also decline during a systemic crisis — typically with a lag — the equity losses modeled in this section understate total equity-like risk in retirement portfolios.

even though all three may intensify simultaneously during a systemic crisis. We estimate that government and agency securities represent approximately 72% of this pool, and corporate bonds approximately 28% (~3.2 trillion).[136] Corporate default rates and mark-to-market impairment assumptions are derived from the IG and HY range in Section 2.2 and Section 2.3, adjusted for retirement portfolio composition. Retirement portfolios hold a more diversified credit mix than the economy-wide corporate bond market—approximately 87% IG and 13% HY.

Table C.5: Retirement Portfolio Corporate Bond Losses ($3.2T outstanding)

Scenario	Blended Default Rate (87/13 IG/HY)	Default Losses ($)	Non-Defaulting Exposure	Blended MTM Rate (87/13 IG/HY)	MTM Losses ($)
Light	0.95%	$30B	~$3.1T	6.3%	$198B
Moderate	1.9–2.0%	$59–62B	~$3.1T	21.2–22.6%	$657–700B
High	2.4–2.7%	$77–87B	~$3.1T	21.2–26.3%	$654–808B
Aggressive	3.4–4.1%	$109–130B	~$3.0–3.1T	21.2–32.6%	$647–990B

Government bond holdings in retirement portfolios are subject to mark-to-market losses from rising long-term interest rates driven by fiscal stress. We apply a duration-based approximation assuming an average portfolio duration of approximately six years, where each 100 basis point rate increase reduces market value by roughly 5.5–6%, with positive convexity moderating losses at larger rate moves.

Table C.6: Retirement Portfolio Government Bond Losses ($8.1T outstanding)

Scenario	Implied Rate Increase (bp)	MTM Rate (%)	MTM Losses ($)
Light	25–50bp	1–3%	$81–$244B
Moderate	75–125bp	4–7%	$325–569B
High	125–200bp	7–12%	$569–976B
Aggressive	175–275bp	10–14%	$813B–1.1T

C.2 Reduced Contributions Methodology

Contribution shortfalls are modeled through two components, estimated over a five-year horizon. Displaced workers lose all retirement contributions—both their own and their employer's match—for the duration of displacement. Workers reclassified from employee to gig or contract status lose employer-sponsored contributions entirely, since independent contractors receive no employer match, and reduce their own contributions in proportion to the wage haircut estimated in Section 1.[137] These shortfalls are the same for the low and high bound within each scenario because they depend on labor market

[136] See footnote above. These are very rough estimates which will need to be refined with further analysis.

[137] Annual shortfalls are calculated as:
Displaced workers: (number displaced) × (average annual combined employer + employee contribution per worker)
Gig-reclassified workers: (number reclassified) × (average annual employer contribution per worker) + (number reclassified) × (average annual employee contribution per worker) × (wage haircut %)

displacement assumptions, not on financial market conditions. In the Light scenario, where no workers are displaced but approximately 15.8 million shift to gig status, the entire shortfall derives from the reclassification channel. Cumulative five-year shortfalls range from $173 billion (Light) to $517 billion (Aggressive).

Match suspensions among remaining employers are calibrated to the GFC, during which approximately 4–6% of plan participants experienced full employer match suspensions. This benchmark is drawn from US Department of Labor Form 5500 filings, which show that the plan-weighted full suspension rate rose from a pre-crisis baseline of approximately 5% to 9% by 2010, while the participant-weighted rate—which better reflects the share of workers actually affected, since larger plans were less likely to suspend—rose from approximately 2% to nearly 4%.[138] Our benchmark of 4–6% represents a blended estimate across these two measures, capturing the crisis-driven suspension rate during a 1× credit stress event. Scaling by scenario-specific credit stress produces suspension rates of approximately 1–2% (Light), 5–8% (Moderate), 9–13% (High), and 12–18% (Aggressive). The Moderate through Aggressive suspension rates exceed the GFC precedent because the Credit Stress metric in those scenarios exceeds 1.0×, reflecting the larger and more sustained nature of AI-driven displacement relative to a cyclical downturn.

Table C.7: Cumulative Contribution Shortfalls (5-Year Horizon)

Scenario	Displaced & Gig Worker Shortfall	Employer Match Suspensions	Total Reduced Contributions
Light	$173B	$18–26B	$190–199B
Moderate	$287B	$67–100B	$354–387B
High	$402B	$107–160B	$509–562B
Aggressive	$517B	$142–213B	$659–730B

C.3 Insurance Assets

Table C.8: Insurance Corporate Bond Defaults

Scenario	Corporate Bond Exposure	Default Losses
Light	~$3.0T	$14B
Moderate	~$3.0T	$30–32B
High	~$3.0T	$41–45B
Aggressive	~$3.0T	$59–69B

[138] Michael J. Brien and Constantijn W. A. Panis, "Defined Contribution Plan Employer Match Suspensions during the Financial Crisis" (Washington, DC: U.S. Department of Labor, Employee Benefits Security Administration, September 2013), Tables 7 and A.10–A.11, https://www.dol.gov/sites/dolgov/files/ebsa/researchers/analysis/retirement/defined-contribution-plan-employer-match-suspensions-during-the-financial-crisis.pdf.

Table C.9: Insurance Corporate Bond Mark-to-Market

Scenario	Non-Defaulting Corp Bonds	MTM Losses
Light	~$3.0T	$120–149B
Moderate	~$3.0T	$208–327B
High	~$3.0T	$326–502B
Aggressive	~$2.9T	$471–674B

Table C.10: Insurance Government/Agency Bond Interest Rate Risk

Scenario	Gov/Agency Holdings	MTM Rate	Losses
Light	~$2.4T	1–3%	$24–72B
Moderate	~$2.4T	4–7%	$96–168B
High	~$2.4T	7–12%	$168–288B
Aggressive	~$2.4T	10–14%	$240–336B

Table C.11: Insurance Equity Portfolio Losses

Scenario	Equity Holdings	Losses
Light	~$1.2T	$237–299B
Moderate	~$1.2T	$719–731B
High	~$1.2T	$856B–1.0T
Aggressive	~$1.2T	$998B–1.1T

Table C.12: Insurance Mortgage and Real Estate Impairment

Scenario	Mortgage/RE Holdings	Impairment Rate	Losses
Light	~$821B	4–9%	$33–74B
Moderate	~$821B	10–18%	$82–148B
High	~$821B	16–27%	$131–222B
Aggressive	~$821B	22–35%	$181–287B

Appendix D: Social Security Trust Fund Depletion Acceleration

We estimate the acceleration of Social Security trust fund depletion using a first-order approximation anchored to the 2025 Trustees Report.[1]

Baseline parameters. The combined OASI and DI Trust Fund reserves stood at $2.72 trillion at year-end 2024. Under the Trustees' intermediate assumptions, the combined funds are projected to be depleted in 2034—approximately 9 years from 2025.[2] This implies an average annual net drawdown of approximately $302 billion per year over the remaining life of the trust funds ($2.72 trillion ÷ 9 years). Note that the current annual deficit is substantially smaller (~$67 billion in 2024), but the Trustees project it to grow rapidly as the ratio of beneficiaries to covered workers increases; the $302 billion figure represents the average drawdown across the entire depletion path, not the starting-year deficit.

Additional payroll tax losses. Each scenario produces an additional annual payroll tax shortfall (L) from two sources: displaced workers who lose all taxable wages, and gig-reclassified workers whose reduced earnings shrink the taxable base. Displacement losses are calculated as (workers displaced) × (average wage of $67,920) × (combined payroll tax rate of 12.4%). Gig wage haircut losses are calculated as (annual wage income lost from gig transition) × 12.4%, reflecting the fact that gig workers remain subject to self-employment tax at the equivalent combined rate but on a lower earnings base.

Acceleration formula. We model the additional losses as a constant annual increment to the baseline drawdown rate. The revised depletion timeline is:
New years to depletion = Reserves ÷ (Baseline average drawdown + Additional annual loss)
Acceleration = Baseline years − New years to depletion = 9 − [$2.72T ÷ ($302B + L)]
This yields:

Table D.1: Estimated Drawdown Severity and Timing Under Alternative Stress Scenarios

Scenario	Additional Annual Loss (L)	Revised Avg Drawdown	New Timeline	Acceleration
Light	$20B	$322B/yr	8.4 yr	~0.6 yr
Moderate	$92B	$394B/yr	6.9 yr	~2.1 yr
High	$156B	$458B/yr	5.9 yr	~3.1 yr
Aggressive	$218B	$520B/yr	5.2 yr	~3.8 yr

Limitations. This is a first-order approximation that assumes the additional payroll tax loss is constant over the remaining life of the trust funds and additive to the baseline drawdown trajectory. It does not account for three effects that would likely accelerate depletion further: (1) early claiming by older displaced workers, which increases outlays simultaneously with reduced inflows; (2) reduced interest earnings as reserves decline faster, creating a compounding effect; and (3) feedback from reduced consumption and GDP contraction on the broader tax base. A full actuarial projection incorporating these dynamics is beyond the scope of this report but would likely produce larger acceleration estimates than those shown above.

---

[1] Board of Trustees, Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds, The 2025 Annual Report of the Board of Trustees (Washington, DC: Social Security Administration, June 2025), https://www.ssa.gov/oact/tr/2025/.

[2] The OASI Trust Fund alone is projected to be depleted in 2033; the DI Trust Fund is not projected to be depleted within the 75-year projection period. We use the combined 2034 date as a conservative baseline, consistent with the Trustees' standard reporting convention.