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AI and the Economy: The Four Rates Which Define The Future

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The economic debate about artificial intelligence has produced a wide range of estimates and almost no coherent framework. This paper bridges that gap.

EXECUTIVE SUMMARY

We provide a unifed modeling about AI macroeconomics impact. Our modeling shows four implications:

AI will displace 19.5–21.5 million workers and generate fiscal capacity that scales with AI speedup. The $2.52 trillion gross productivity uplift ($2.01–2.17 trillion net of demand drag) generates incremental federal tax capacity that exceeds the displaced workers' permanent income loss at base case speedup (s = 1.38) and grows further at higher s. We show that a faster, more capable AI strengthens the fiscal position while leaving the number of displaced workers unchanged.

AI will be more deflationary than the China trade shock, and more permanent. The combined supply and demand channels produce an average deflationary impulse of more than −1% per year; more than 50% larger than China's peak contribution to US disinflation (hitting services rather than goods).

AI's footprint is already measurable in current data. We document $642 billion in excess productivity above pre-2022 trend, 2.9 million missing jobs in high-exposure sectors, and wages decoupling from productivity in direct proportion to each sector's automation ceiling.

A coherent framework for the AI debate. Via a single framework, we endogenously derive the impact of AI on GDP, jobs, prices, and vendor economics, producing internally consistent forecasts.

Link to scenario tool here: AI Macro Impact App. This is a condensed version of a full paper available on SSRN: here.

INTRODUCTION

The economic debate about artificial intelligence has produced a wide range of estimates and almost no coherent framework. Goldman Sachs (Briggs and Kodnani 2023) sees 7% global GDP growth. Academic research (Acemoglu 2024) sees 0.71% TFP gains over a decade. McKinsey counts $2.6–4.4 trillion in corporate value. The IMF (2025) brackets a range so wide it barely constrains the debate. These estimates differ by a factor of ten or more because they focus on the wrong input variable and lack a coherent analytical framework.

The dominant approach treats AI's economic impact as a function of its capability. Electricity was capable in 1882. The computer was capable in the 1950s. Neither appeared in productivity statistics for decades. The binding constraint in every prior General Purpose Technology transition was never the technology; it was the pace at which firms and workers reorganized around it. Measuring capability tells you the ceiling. It tells you nothing about the path, the timing, or the distribution of gains along the way.

This paper addresses each of those gaps. We develop a Four-Rate Framework comprising Innovation, Deployment, Adoption, and Displacement rates, and combine it with the notion of Workflow Completeness (C^*), a bottom-up sectoral automation ceiling derived from Amdahl's Law applied to labor economics.[1] We calibrate the framework against three empirical signals already visible in current US data, producing a single internally consistent set of macroeconomic forecasts spanning the full economy.

FRAMEWORK

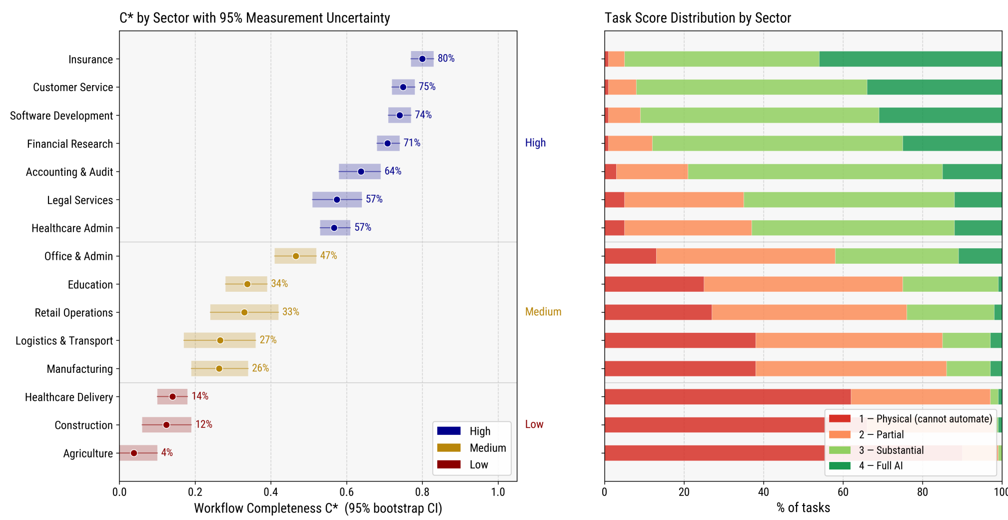
Every major technology transition follows the same pattern. While the Innovation Rate may capture public attention, it is the Deployment, Adoption, and Displacement rates that drive economic impact. The productivity gains from electricity did not appear until the 1920s, forty years after Edison's first generator, because factories had to be physically rebuilt around the new power source before the gains could materialise. Computing followed the same

1. Amdahl's Law, originally formulated by Gene Amdahl (1967) to describe the limits of parallel computing, states that the maximum speedup of a system is bounded by the fraction that cannot be parallelized. If 80% of a computation can be parallelized and 20% must remain serial, even infinite parallel processing delivers only a 5× improvement. Applied to labor: if AI can automate 80% of a workflow's tasks but 20% require physical presence, regulatory sign-off, or human judgment, the productivity gain is bounded by that 20% serial constraint regardless of how capable the AI becomes.

arc: mainframes arrived in the 1950s, but the productivity boom did not come until firms stopped bolting computers onto existing processes and redesigned workflows around information flow.

Four Rates. AI is no different. The binding constraint is not capability; it is the pace of organizational adaptation. We decompose the AI transition into four observable rates: the *Innovation Rate* (how fast AI becomes capable), the *Deployment Rate* (how fast organizations give workers access to AI tools), the *Adoption Rate* (how fast workflows are actually redesigned to generate productivity gains), and the *Displacement Rate* (how fast AI replaces rather than augments human labor). Each rate is distinct, each is measurable, and each is currently at a different level. The gaps between them define where the economy stands in the transition.[2]

Workflow Completeness. We define Workflow Completeness (*C**) as the maximum fraction of any sector's tasks that AI can ultimately automate, regardless of how fast the rates converge. Derived from Amdahl's Law applied to labor economics, *C** is a structural ceiling, not a forecast. Prior task-based exposure estimates measure what AI can do today. Instead, *C** measures the maximum fraction of a workflow that AI can ever automate, given the physical, regulatory, and relational constraints that no software can substitute. It does not move with model capability. A more powerful AI model does not perform surgery, sign legal documents, or lay concrete. *C** is determined by the composition of the work, not the state of the technology. We estimate *C** from O*NET labor description data, which leads to Customer Service reaching 75%, Professional Services 67%, and Construction only 12%.



Sources: O*NET Task Statements (Release 29.0, 18,796 task statements) · OEWS May 2024 employment weights · Scored by Claude using 4-point automation scale anchored to confirmed deployments
95% CI from task-level bootstrap (2,000 draws) · Validated against Eloundou et al. (2023) E2 scores (Spearman rank correlation 0.95)
Tier thresholds: High >=55%, Medium 25-55%, Low <25%. Liminal Capital Research, 2026.

Macro Identity. Finally, our framework relies on a macroeconomic identity: every dollar of value AI generates must go somewhere. Formally:

$$\text{Gross GDP Uplift} = \text{AI Vendor Revenue} + \text{Corporate Margin} + \text{Consumer Deflation} - \text{Displaced Wage Bill}$$

Every dollar flows to one of four destinations: AI vendors as software revenue, firms as margin, consumers as lower prices, or out of the economy entirely as displaced workers lose income they would otherwise have spent. All forecasts in this paper are derivations of one term in that identity, governed by the same four rates.

THE DATA: AI'S FOOTPRINT IS ALREADY VISIBLE

Contrary to the prevailing view, our research shows that AI's economic impact is not a future event and its footprint is already substantial. We identify three independent signals below.

2. Each rate is modelled as a logistic function of C^*: $\text{Rate}(t) = C^* \times L / (1 + \exp(-\lambda(t - t_{mid})))$, where C^* sets the structural ceiling, L is the saturation share of that ceiling reached at equilibrium, λ is the diffusion speed, and t_{mid} is the inflection year. At any point in time: Deployment Rate ≈ 0.31 × C^* (2026 observed, Massenkoff and McCrory 2026); Adoption Rate ≈ 0.27 × C^* (2026 empirical anchor, McKinsey 2025); Displacement Rate ≈ 0.026 × C^* (2026 observed). All three rates converge toward C^* at equilibrium but at different speeds governed by their respective λ parameters.

Productivity. Sectors with higher Workflow Completeness show significantly larger post-2022 productivity acceleration. Using BEA value-added data (Bureau of Economic Analysis 2024), fitting a log-linear trend over 2015–2019 and measuring deviations since ChatGPT's launch, we find that C^* alone explains 82% of cross-sectoral productivity variance (γ = 9.37, R^2 = 0.72, p = 0.0018, n = 9). High-exposure sectors are running 10–12 percentage points above their pre-ChatGPT trend. Information and Technology is up 11.0pp. Finance and Insurance up 7.7pp. Construction, with a C^* of 12%, is near zero. The relationship did not exist before 2022, combining to a $642 billion productivity impact on GDP already observable. The most credible alternative, Fed tightening forcing firms to extract more output from existing workers, is ruled out: capital sensitivity proxies are statistically unrelated to the productivity acceleration (ρ = −0.05, p = 0.90), while AI exposure explains it precisely (ρ = +0.63, p = 0.07).

Employment. High-C^* sectors are running 2.9 million jobs below their pre-pandemic trend, while sectors that hired identically during the COVID surge are still growing, consistent with Levanon (2026) and Brynjolfsson, Chandar, and Chen (2025), who document the same hiring gate effect using independent BLS (Bureau of Labor Statistics 2024) and Stanford Digital Economy Lab data, respectively. The mechanism is not layoffs; layoff rates are flat across all sectors. It is a hiring gate: firms are producing more with the same people and simply not replacing departing workers. The most credible alternative, the pandemic over-hiring hypothesis, cannot explain this: high-C^* sectors did not over-hire post-COVID relative to low-C^* sectors (p = 0.966), yet they are the ones with suppressed hiring now. Transport and Logistics, which over-hired more than any other sector during the pandemic, is still adding jobs. Information and Technology, which over-hired half as much, is 270,000 below trend.

Wages. In a normal competitive labor market, productivity gains flow to workers. In the Adoption phase of a General Purpose Technology transition, firms capture the surplus before workers can bargain for it. We find a wage-productivity decoupling proportional to C^* with R^2 = 0.64 (p = 0.005). Workers in Information and Technology are producing 11.0 percentage points more per year than their pre-2022 trend while their wages grow below the economy average. In Construction the reverse holds, exactly what competitive market theory predicts when AI has little to automate. The most credible alternative, mean reversion of the productivity gap, cannot account for this pattern: the gap was near zero at ChatGPT's launch, has widened every single quarter since, and now stands at +20pp eleven quarters later with no sign of plateau (Kendall τ = +1.00, p < 0.001).

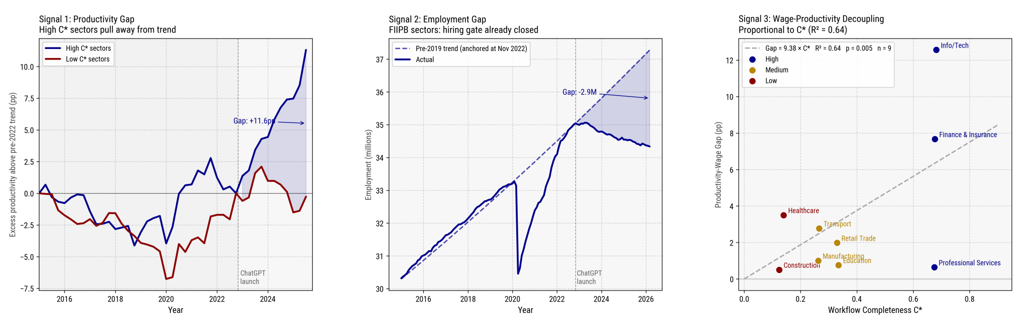
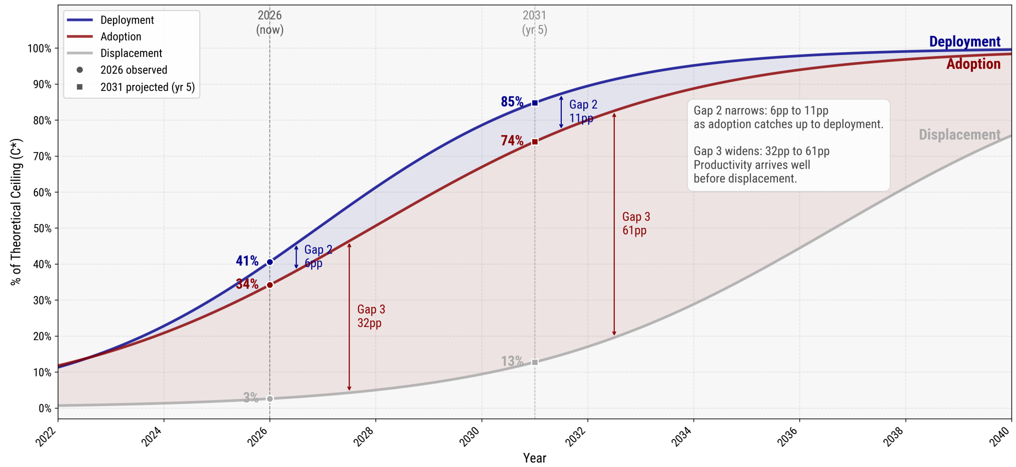


Figure 2: Three Empirical Signals: Productivity, Employment, and Wage–Productivity Decoupling

Taken together, these three datasets point in the same direction, appearing at the same inflection point in late 2022, while potential alternative hypotheses have been ruled out. These three signals do more than confirm AI's current footprint. They also provide the empirical anchors that calibrate the model parameters in the next section. The adoption rate is pinned to the productivity regression, the displacement anchor to the employment gap, and the wage data validates the C^* tier ordering.

FORECASTS

What distinguishes our modeling is the ability to generate endogenously consistent macroeconomic forecasts across different macro indicators. Every figure below emerges from the same four-rate framework, calibrated to the empirical signals documented in the previous section. GDP, jobs, prices, and AI vendor economics are derived from a single set of parameters, consistent with each other by construction.



Sources: Deployment: Anthropic usage data (2026), 31% of C* at 2025, λ=0.42/yr. Adoption: McKinsey State of AI (Mar 2025), 0.27 × C* at 2026, λ=0.34/yr
Displacement: BLS OEWS (May 2024), 0.026 × C* at 2026, λ=0.34/yr. Curves: L(t) = C* / (1+e^(−λ(t−t_mid))). Liminal Capital Research, 2026.

Figure 3: Three Economic Rates from the Four-Rate Framework: Deployment, Adoption, and Displacement

Figure 3 illustrates how the three rates are affecting the economy and the central tension of the current moment. Deployment is largely complete across large organizations. Adoption is accelerating but only 27% of workflows have been genuinely redesigned. Displacement has barely begun, currently at 2.6% of the automatable ceiling. The gap between Adoption and Displacement is the window during which firms produce more with the same people, before competitive pressure forces them to right-size.[3]

GDP. At long-run equilibrium, we expect AI to generate a gross productivity uplift of approximately $2.52 trillion, or roughly 9% of current US GDP. After deducting the demand drag from displaced worker income, the net impact is $2.01–2.17 trillion deterministic (λ = 0.35–0.50), with a Monte Carlo P25–P75 range of $1.54–2.48 trillion. At the five-year horizon, the model produces $1.34–1.85 trillion in gross uplift (Monte Carlo P25–P75; central $1.59 trillion deterministic), with displacement still modest enough that gross and net figures remain close. The early phase is dominated by productivity gains. The compression comes later, as displacement accelerates.

Labor. Structural displacement at long-run equilibrium reaches 19.5–21.5 million workers (Monte Carlo P25–P75; central 20.5 million), concentrated in white-collar, graduate-educated professionals averaging approximately $75,000 in wages.[4] This is not the manufacturing automation of the 2000s, which hollowed out occupations already losing political influence. The $529–717 billion per year in revenue flowing to AI vendors translates, at the revenue-per-employee ratios observed at leading AI companies, into a workforce of approximately 415,000–1,660,000 people. That is the labor force that partially replaces 19.5–21.5 million displaced workers: 12 to 50 times smaller, geographically concentrated in a handful of technology hubs, and with a marginal propensity to consume of approximately 0.30 versus the 0.68 of the middle-income professionals it displaces.

Prices. AI is deflationary through two distinct channels. The supply side produces a permanent price level reduction of 7.0–7.9% at equilibrium as unit costs fall through a combination of productivity gains and workforce right-sizing. The demand side produces an ongoing inflation drag of 0.66–0.94% per year from the income loss of displaced workers. Both channels build gradually, do not reverse, and become self-reinforcing through the Displacement phase. On average across the transition, the combined channels produce a deflationary impulse of more than 1% per year, more than 50% larger than the Chinese goods deflation impulse of around 0.5%, and hitting services rather than goods.

AI Vendor Revenue. The revenue pool available to AI vendors at long-run equilibrium is $529–717 billion per year (Monte Carlo P25–P75; central $623 billion), derived not from software budget displacement but from the value AI creates by substituting human capital with technology. At five years the deterministic central range is $180–360

3. Each rate follows a logistic diffusion process: f(t) = C^* × L / (1 + exp(−λ(t − t_mid))), where C^* is the Workflow Completeness ceiling, λ is the diffusion speed, and t_mid is the inflection point. All parameters are calibrated directly to observable data. From these three curves all four macroeconomic forecasts are derived endogenously through the accounting identity.
4. BLS Occupational Employment and Wage Statistics, May 2024. Employment-weighted mean annual wage across Finance and Insurance, Professional Services, and Information sectors.

billion (median $226 billion). Vendors are the single most structurally advantaged participant in this transition: they extract their share before competitive pass-through forces productivity gains to consumers, and their position compounds with each wave.

Distributional reality. AI vendors and consumers are the long-run beneficiaries. Workers in high-exposure sectors bear the adjustment cost. Early-adopting firms capture temporary margin that competition eventually erodes. The shift from a large, geographically dispersed, high-spending displaced workforce toward a small, concentrated, lower-spending AI workforce creates a persistent gap between gross output and aggregate demand. That gap is the policy challenge. The productivity surplus the transition generates is the resource available to close it.

The dominant source of uncertainty across all four forecasts is a single parameter: the task-level productivity speedup AI delivers, that is, the factor by which AI reduces the time required to complete an automatable task. Our central estimate of 1.38× is deliberately conservative, anchored to observed deployment data, our own BEA cross-sectional regression, and consistent with McKinsey's observed data.

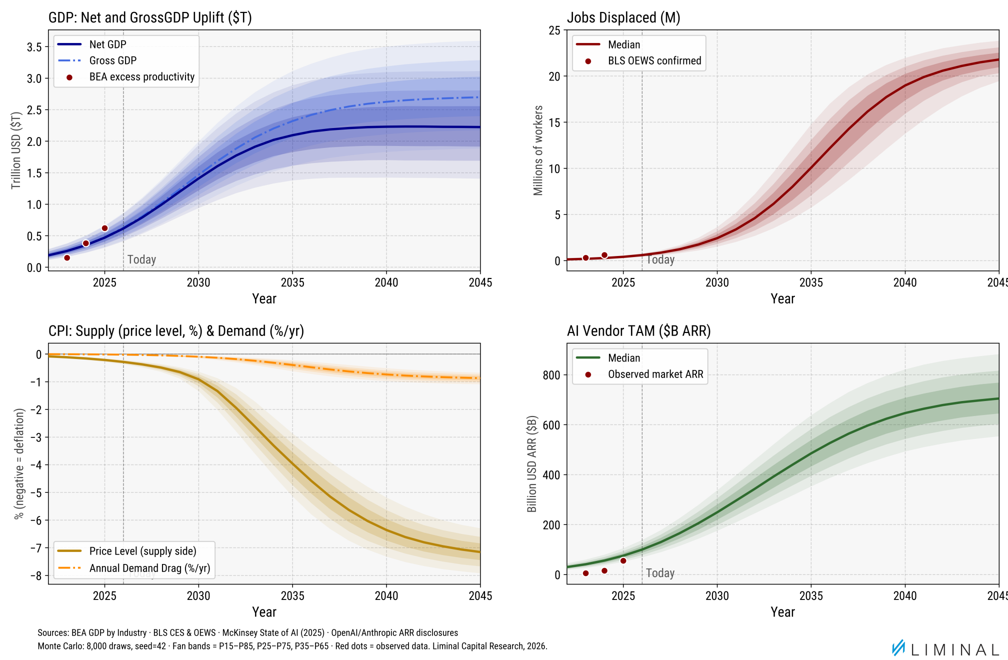


Figure 4: Monte Carlo Trajectories: Net GDP, Jobs Displaced, CPI, and AI Vendor Revenue (P15–P85 bands)

POLICY IMPLICATIONS

While a higher AI speedup generates more surplus for the economy, it does not increase the number of displaced workers. Prosperity and displacement are governed by orthogonal parameters: the productivity surplus scales with AI capability, while jobs displaced are determined by C^* and the structural composition of work alone (a full illustration is provided in Appendix A).

This has a direct policy implication. Restricting AI capability reduces the surplus available to support displaced workers without reducing their number. It is not a trade-off; it makes the economy strictly worse off for the workers it claims to protect.

The constructive policy levers are deregulation in low-C^* sectors (Construction, Healthcare Delivery, skilled trades) to absorb displaced workers, and acceleration of AI adoption in the broader economy to bring consumer deflation forward. Both are market-compatible and require no new institutions.

On monetary policy, the two deflationary channels require distinct responses. Supply-side deflation from productivity gains is a positive supply shock and warrants lower long-term rates, not stimulus. Demand-side deflation from income destruction is structural and requires fiscal redistribution, not rate cuts. The AI transition is structurally different from both COVID (a concurrent collapse of supply and demand that self-corrected as restrictions lifted) and 2008 (a pure demand shock). Recognizing that distinction is the foundation of a calibrated policy response.

Our four-rate framework provides a map for policymakers: it shows which rate is the binding constraint at any point in the transition and therefore which instrument to deploy and when.

CONCLUSION

The debate about AI's economic impact has generated more heat than light because it has so far lacked the right variable, the right framework, and the right data simultaneously. This paper provides all three: a Four-Rate Framework that identifies the binding constraints others have missed, three independent empirical signals already visible in current data, and a unified set of forecasts derived from a single coherent model.

AI's economic footprint is already measurable in current data: $642 billion in productivity gains, 2.9 million missing jobs, a wage-productivity decoupling proportional to each sector's automation ceiling. Our modeling captures the interactions between productivity gains ($2.52 trillion gross, $2.01–2.17 trillion net of demand drag), labor displacement (19.5–21.5 million jobs), price dynamics (cumulative supply-side reduction of 7–8% plus ongoing demand drag), and AI vendor economics ($529–717 billion in annual revenue).

The deflationary consequences alone are without precedent in the modern era. China's integration into global trade produced a sustained disinflationary impulse of roughly 0.5% per year on the US consumer basket, an effect that held inflation structurally below target for a decade. AI is expected to produce more than twice that annual flow during the transition, hitting services rather than goods. Critically, unlike the China shock where the productivity gains accrued abroad, AI's gains stay in the domestic economy, large enough to more than offset the income shock for those displaced.

The history of General Purpose Technology transitions offers a consistent lesson: economic impact lags technological capability, and the lag is determined primarily by organizational adaptation rather than by the technology itself. The four rates presented here are not merely an analytical tool; they are a map for understanding and navigating what comes next.

APPENDIX A: FISCAL CAPACITY ACROSS SPEEDUP SCENARIOS

The framework's central policy finding is that prosperity and displacement are governed by orthogonal parameters. The table below makes this concrete: fiscal capacity grows with s, the AI task speedup, while jobs displaced remain invariant to s by construction.

	s = 1.20	s = 1.38	s = 1.50	s = 2.00
Gross GDP uplift	$1.43T	$2.52T	$3.18T	$5.42T
Tax revenue (20%)	$285B	$505B	$636B	$1,084B
Jobs displaced	20.5M	20.5M	20.5M	20.5M
Net displaced wage bill	$438B	$438B	$438B	$438B
Tax coverage	**0.65×**	**1.15×**	**1.45×**	**2.48×**

Table 1: Tax fiscal capacity vs. displaced wage bill across speedup scenarios (long-run equilibrium). Tax revenue applies a 20% blended effective federal rate to gross GDP uplift, consistent with the circular flow identity. Net displaced wage bill = wages × λ = $1.25T × 0.35 ≈ $438B, with λ = 0.35 the central ADH income loss rate for professional-class workers. At the upper-bound rate of λ = 0.50 the wage bill rises to $625B and base-case coverage falls to 0.66×. Jobs displaced invariant to s by construction. All figures long-run equilibrium, 2026 dollars.

At base case (s = 1.38) the framework's fiscal-capacity calculation covers approximately 115% of the permanent displaced-income loss at the central ADH rate of 0.35, with the ratio falling to 0.65× at s = 1.20. As s increases the ratio grows to 2.48× at s = 2.00. Within the model, the resources scale directly with s while the displaced wage bill stays fixed.

APPENDIX B: MODEL DERIVATIONS

JOBS AT RISK

$$\text{Jobs}(t) = \text{Employment} \times C^* \times \lambda_d(t) \times \alpha$$

where $\lambda_d(t)$ is the Displacement Rate logistic at time t (fraction of C^* converting to headcount reduction); $\alpha = 0.75 \times 0.75 = 0.5625$ is the structural retention floor, reflecting a 25% floor of irreplaceable management and client-facing roles and one new oversight role created per four displaced. At the five-year horizon $\lambda_d = 0.13 \times C^*$, giving Jobs(5yr) = Employment × 0.0717 × C^*.

GDP UPLIFT

$$S(f) = 1 / [(1 - f) + f/1.38]$$

where $f = \lambda_a(t) \times C^*$ is the fraction of the workflow covered at the current Adoption Rate; 1.38 is the task-level speedup (midpoint of McKinsey observed gains and BEA cross-sectional OLS). $S(f) - 1$ is the productivity gain per worker.

$$\text{GDP Drag}(t) = \text{Displaced Wage Income}(t) \times \lambda \times MPC \times \kappa$$

where $\lambda = 0.35$ is the effective income loss rate for displaced professional-class workers (Autor, Dorn, and Hanson 2016); $MPC = 0.68$ (Federal Reserve Survey of Consumer Finances 2022); $\kappa = 1.20$ is the consumption multiplier (Congressional Budget Office 2024).

$$\text{Net GDP}(t) = \text{GDP Uplift}(\lambda_a(t)) - \text{GDP Drag}(\lambda_d(t))$$

CPI

$$\Delta\text{Unit Cost}(t) = 1 - [1 - \lambda_d(t) \cdot \alpha] / S(\lambda_a(t))$$

Output expansion via the Adoption Rate reduces the denominator of unit cost before any displacement occurs. Wage bill contraction via the Displacement Rate reduces the numerator. Both compound on the same expression.

$$\Delta P_{\text{supply}}(t) = \Delta\text{Unit Cost}(t) \times PT(f), \quad PT(f) = 0.30 + 0.60 / [1 + e^{-12(f - 0.75)}]$$

where $PT(f)$ is the competitive pass-through rate, rising logistically from ~30% (early adopters retain margin) to ~85% (industry-wide adoption forces price competition).

$$\Delta P_{\text{demand}}(t) = -[\text{Jobs}(t) \times \bar{W} \times \lambda \times MPC \times \kappa] / (C \times \varepsilon)$$

where $\bar{W}$ = \$61,000 is the employment-weighted average wage of at-risk workers; *C^* = \$19 trillion nominal consumer spending; $\varepsilon = 0.35$ is the price elasticity of demand.

$$\Delta P_{\text{total}}(t) = \Delta P_{\text{supply}}(t) \text{ [stock]} + \Delta P_{\text{demand}}(t) \text{ [flow/yr]}$$

AI VENDOR REVENUE

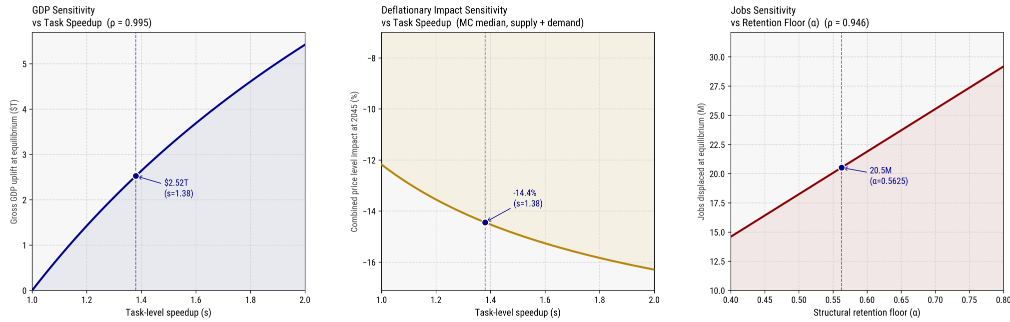
$$\text{TAM}(t) = \text{Pool 1}(t) + \text{Pool 2}(t)$$

Pool 1 = GDP Uplift(t) × [0.10, 0.20], where [0.10, 0.20] is the mature-market vendor capture rate applied before competitive pass-through.

Pool 2 = Displaced Wage Bill(t) × 1.30 × [0.10, 0.20], where 1.30 is the employer cost multiplier converting employee wages to total labor cost.

APPENDIX C: SENSITIVITY ANALYSIS

We review here the sensitivity of our forecasts to the key parameters. GDP is mostly sensitive to the task-level speedup *s*, CPI is mostly sensitive to *s* as well while the jobs displaced is mostly sensitive to the structural retention floor *α*.



Sources: Amdahl formula across 9 BEA sectors (GDP); MC simulation 8,000 draws (CPI); BLS OEWS employment weights (Jobs). Base case: s=1.38, α=0.5625. CPI combines supply-side stock and cumulated demand drag at 2045. Liminal Capital Research, 2026.

Figure 5: Key Model Sensitivities: GDP, CPI, and Jobs Displaced

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