AI Development, Energy Markets, and Macroeconomy: A Dynamic General Equilibrium Analysis*

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Abstract

This note quantifies the interplay between AI development, capital accumulation, and energy markets using a three-sector dynamic general equilibrium model calibrated to the Japanese economy. We analyze steady-state shifts driven by a 100 times increase in AI productivity. Our analysis yields four primary findings. First, while Real GDP expands to 2.5 times its initial level, household welfare gains are more modest because the AI-intensive economy necessitates a higher investment share at the expense of household consumption. Second, we identify a quantitative "Jevons paradox": while technological development enhances the energy efficiency of AI, the volume effect of AI demand and the resulting intensified energy consumption drive energy prices up by nearly 7 times. Third, the shift to the new AI-intensive economy induces a huge structural decline in the labor income share from 55% to 31%. Finally, these outcomes are highly sensitive to the elasticity of substitution between labor and AI; a 5% increase in the elasticity doubles the energy price response, highlighting the uncertainty inherent in the shift to an AI-driven era.

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1 Introduction

The explosive growth of Artificial Intelligence (AI) has raised urgent concerns about its physical footprint, particularly the soaring energy demand of data centers and computational infrastructure. While the potential for AI to drive productivity is widely acknowledged, critical questions remain regarding the sustainability of this growth under resource constraints. To what extent will the energy appetite of AI dampen its economic benefits? Addressing this requires moving beyond qualitative debate. This note provides a quantitative assessment of the interplay between AI development, capital accumulation, and energy markets.

We develop a three-sector dynamic general equilibrium model to numerically evaluate how AI productivity shocks transmit through the economy, explicitly measuring the magnitude of trade-offs between growth and energy costs. We calibrate our model to the Japanese economy and simulate a change in the steady state equilibrium driven by a 100 times increase in AI productivity. Our quantitative analysis yields four critical findings regarding the magnitude of this change. First, we show that Real GDP expands by a factor of 2.5 due to efficient production using AI. However, we also show that the increase in welfare is not as much as that of GDP, because the new AI-intensive steady state necessitates a higher investment share at the expense of consumption. Second, energy constraints bind tightly; we quantify a "Jevons paradox" where energy prices surge nearly 7 times due to the volume effect of AI demand, dominating efficiency gains. Third, the transition induces a structural shift that drives a continuous decline in the labor income share as the economy becomes increasingly capital-intensive. Finally, we find that these outcomes are highly sensitive to structural parameters: a modest 0.1-point increase in the labor-AI substitution elasticity quantitatively doubles the energy price response, highlighting the fragility of the energy market to AI integration.

A nascent macroeconomic literature examines how advances in AI reshape productivity and factor allocation. Recent studies suggest that AI and automation can boost aggregate productivity but also alter the input mix of production (Acemoglu and Restrepo, 2018, 2020; Aghion et al., 2023; Acemoglu and Johnson, 2024; Aghion et al., 2025; Acemoglu, 2025). At the same time, researchers have begun to explore the resource constraints of AI: Bogmans et al. (2025), in particular, use a multi-country general equilibrium model to show that the proliferation of AI-intensive industries (such as data centers) can significantly increase energy consumption and prices. Our study contributes to this literature by developing a transparent three-sector dynamic general equilibrium model calibrated to Japan and by quantifying the general equilibrium effects and energy market impacts of large AI productivity shocks. Despite the simplicity of our framework, it provides rich implications for AI development regarding factor allocation and energy markets.

2 Model

We develop a three-sector dynamic general equilibrium model with endogenous investment. The model features a nested constant elasticity of substitution (CES) production structure in the general sector that allows for separate treatment of capital-labor substitution and labor-AI substitution.

2.1 Representative Household

The representative household maximizes lifetime utility over consumption of general goods ($C_{General}$) and energy (C_{Energy}), and chooses investment (I) to accumulate capital. The household owns labor, capital, and the fixed amount of the energy endowment $\bar{E}$:

$$\max_{\{I_t, C_{General,t}, C_{Energy,t}\}} \quad \sum_{t=0}^{\infty} \beta^t U(C_{General,t}, C_{Energy,t}) \tag{2.1}$$

$$\text{s.t.} \quad C_{General,t} + P_{Energy,t} C_{Energy,t} + I_t = w_t \bar{L} + r_t K_t + P_{Energy,t} \bar{E} \tag{2.2}$$

$$K_{t+1} = I_t + (1 - \delta_K) K_t \tag{2.3}$$

where the period utility is CES:

$$U(C_G, C_E) = \left(C_G^{\frac{\sigma_{HH}-1}{\sigma_{HH}}} + C_E^{\frac{\sigma_{HH}-1}{\sigma_{HH}}} \right)^{\frac{\sigma_{HH}}{\sigma_{HH}-1}} \tag{2.4}$$

Here β is the discount factor, δ_K is the capital depreciation rate, and the numeraire is the price of general goods ($P_{General} = 1$).

2.2 Production Sectors

2.2.1 General Sector (Nested CES)

The general sector produces goods $y_{General}$ using capital (K_G), labor (L), and AI services (x_{AI}) with a nested CES production function:

Outer level: Capital and the labor-AI composite (H) are combined with elasticity σ_{outer}:

$$y_{General} = \phi_{General} \left[\alpha \cdot K_G^{\frac{\sigma_{outer}-1}{\sigma_{outer}}} + (1-\alpha) \cdot H^{\frac{\sigma_{outer}-1}{\sigma_{outer}}} \right]^{\frac{\sigma_{outer}}{\sigma_{outer}-1}} \tag{2.5}$$

where $\alpha \in (0, 1)$ is the capital share parameter.

Inner level: The labor-AI composite H combines labor and AI services with elasticity σ_{inner}:

$$H = \left[L^{\frac{\sigma_{inner}-1}{\sigma_{inner}}} + x_{AI}^{\frac{\sigma_{inner}-1}{\sigma_{inner}}} \right]^{\frac{\sigma_{inner}}{\sigma_{inner}-1}} \tag{2.6}$$

2.2.2 AI Sector (Symmetric CES)

The AI sector produces AI services y_{AI} using energy (x_{Energy}) and capital (K_{AI}) with a symmetric CES production function:

$$y_{AI} = \phi_{AI} \left(x_{Energy}^{\frac{\sigma_{AI}-1}{\sigma_{AI}}} + K_{AI}^{\frac{\sigma_{AI}-1}{\sigma_{AI}}} \right)^{\frac{\sigma_{AI}}{\sigma_{AI}-1}} \tag{2.7}$$

where ϕ_{AI} is the AI sector productivity, and $\sigma_{AI} < 1$ implies energy and capital are complements in AI production. The symmetric specification (equal weights on energy and capital) is a natural benchmark that reduces the number of free parameters.

2.2.3 Capital Allocation

Total capital is allocated between the two sectors:

$$K = K_G + K_{AI} \tag{2.8}$$

In equilibrium, capital earns the same return in both sectors.

2.3 Competitive Equilibrium

A Competitive Equilibrium is a set of prices and allocations such that:

1. **Household Optimization:** The household maximizes utility subject to the budget constraint and capital law of motion.

2. **Firm Profit Maximization:**

   - General sector: $\max_{K_G, L, x_{AI}} P_{General} \cdot y_{General} - r \cdot K_G - w \cdot L - P_{AI} \cdot x_{AI}$
   - AI sector: $\max_{K_{AI}, x_E} P_{AI} \cdot y_{AI} - r \cdot K_{AI} - P_{Energy} \cdot x_{Energy}$

3. **Market Clearing:**

$$C_{General} + I = y_{General} \qquad \text{(Goods Market)} \tag{2.9}$$
$$x_{AI} = y_{AI} \qquad \text{(AI Market)} \tag{2.10}$$
$$C_{Energy} + x_{Energy} = \bar{E} \qquad \text{(Energy Market)} \tag{2.11}$$
$$K_G + K_{AI} = K \qquad \text{(Capital Market)} \tag{2.12}$$

4. **Law of Motion:** $K_{t+1} = I_t + (1 - \delta_K)K_t$

2.4 Steady State

In this note, we focus on a steady state for simplicity. In steady state, we have $K_{t+1} = K_t = K$, which implies $I = \delta_K K$. We also have $r = \rho + \delta_K$ from the Euler equation in the steady state.

3 Calibration

We calibrate the model's steady state to match key characteristics of the Japanese economy. Table 1 summarizes all model parameters. Regarding the elasticity of substitution parameters, we rely on empirical estimates to capture the technological structure of the economy. We set the household elasticity of substitution between general goods and energy, σ_{HH}, to 0.58, following the meta-analysis by Labandeira et al. (2017). In the general production sector, the outer-level elasticity between capital and the labor-AI composite, σ_{outer}, is set to 0.9, consistent with the estimates for the Japanese economy by Miyake and Osumi (2020). The inner-level elasticity between labor and AI services, σ_{inner}, is set to 2.05, reflecting the substitutability between robots and employment found by Adachi et al. (2024). For the AI sector, we assume a relatively low elasticity of substitution between energy and capital by setting σ_{AI} to 0.52, based on Koetse et al. (2008).

For the dynamic parameters, we adopt standard values used in business cycle accounting for Japan. Specifically, we set the subjective discount factor β to 0.97 and the capital depreciation rate δ_K to 0.09, following Hayashi and Prescott (2002). We normalize the labor endowment $\bar{L}$ and the general sector TFP $\phi_{General}$ to unity. The remaining structural parameters are jointly calibrated to target specific steady-state moments. The capital share parameter in the general sector, α, is set to 0.518 to match a labor income share of 55%. The energy endowment $\bar{E}$ is calibrated to 71.40, targeting the household's energy expenditure share of 5.5%. Finally, the baseline AI sector productivity ϕ_{AI} is calibrated to 0.000399 to match an AI revenue share of GDP of 0.224% as of 2024 in Japan.

Table 1: Model Parameters

Parameter	Description	Value	Target/Source
Elasticity of Substitution			
σ_{HH}	Household (General vs Energy)	0.58	Labandeira et al. (2017)
σ_{outer}	General sector (Capital vs Labor-AI)	0.9	Miyake and Osumi (2020)
σ_{inner}	General sector (Labor vs AI)	2.05	Adachi et al. (2024)
σ_{AI}	AI sector (Energy vs Capital)	0.52	Koetse et al. (2008)
Dynamic Parameters			
β	Discount factor	0.97	Hayashi and Prescott (2002)
δ_K	Capital depreciation	Set	Hayashi and Prescott (2002)
Normalized Parameters			
$\bar{L}$	Labor endowment	1.00	—
$\phi_{General}$	General sector TFP	1.00	—
Calibrated Parameters (3 params $\rightarrow$ 3 targets)			
α	Capital share (outer CES)	0.518	Labor share = 55%
$\bar{E}$	Energy supply	71.40	Energy consumption share = 5.5%
ϕ_{AI}	AI sector TFP (baseline)	0.000399	AI GDP share = 0.224%

4 Counterfactual: Higher AI Productivity

In this section, we examine the steady-state effects of increasing AI productivity (ϕ_{AI}) from its baseline level up to a 100 times increase. Figure 1 summarizes the responses of key macroeconomic variables, normalized to their baseline values.

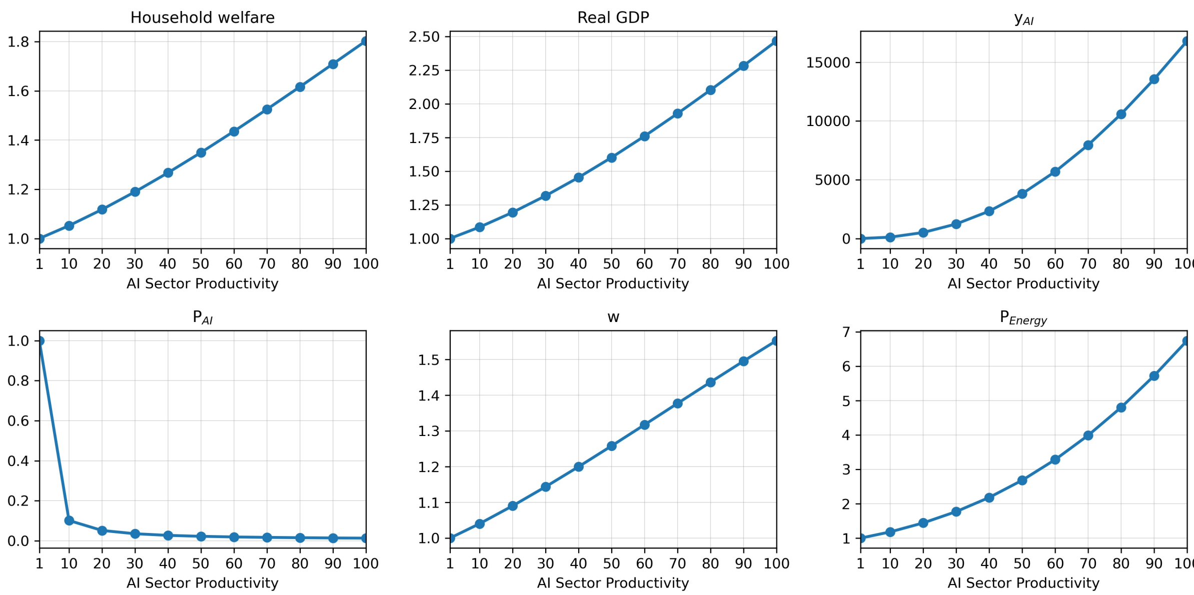

Figure 1: Counterfactual responses to higher AI productivity, normalized to baseline.

As shown in the upper panels of Figure 1, a 100 times increase in AI TFP raises household welfare by a factor of 1.8 and Real GDP by a factor of 2.5. The divergence between the GDP and welfare responses is driven by investment dynamics. Specifically, the rapid expansion of the AI sector necessitates significant capital accumulation. Consequently, a larger portion of output is allocated to investment rather than consumption, causing welfare gains to lag behind GDP growth.

The lower panels of Figure 1 depict price responses. As expected, technological improvements drastically reduce the price of AI services (P_{AI}). This price reduction stimulates strong demand from the general goods sector, pushing up the wage rate (w).[1]

Notably, the price of energy (P_{Energy}) surges significantly. This outcome is consistent with the "Jevons paradox." Although improvements in AI TFP make AI production more energy-efficient per unit of output, the substantial decline in AI prices induces a disproportionately large increase in demand for AI services. This volume effect dominates the efficiency gain, resulting in higher aggregate energy demand and a sharp rise in energy prices.

[1] The interest rate r is pinned down by the household's Euler equation in the steady state, and it does not respond to the AI productivity.

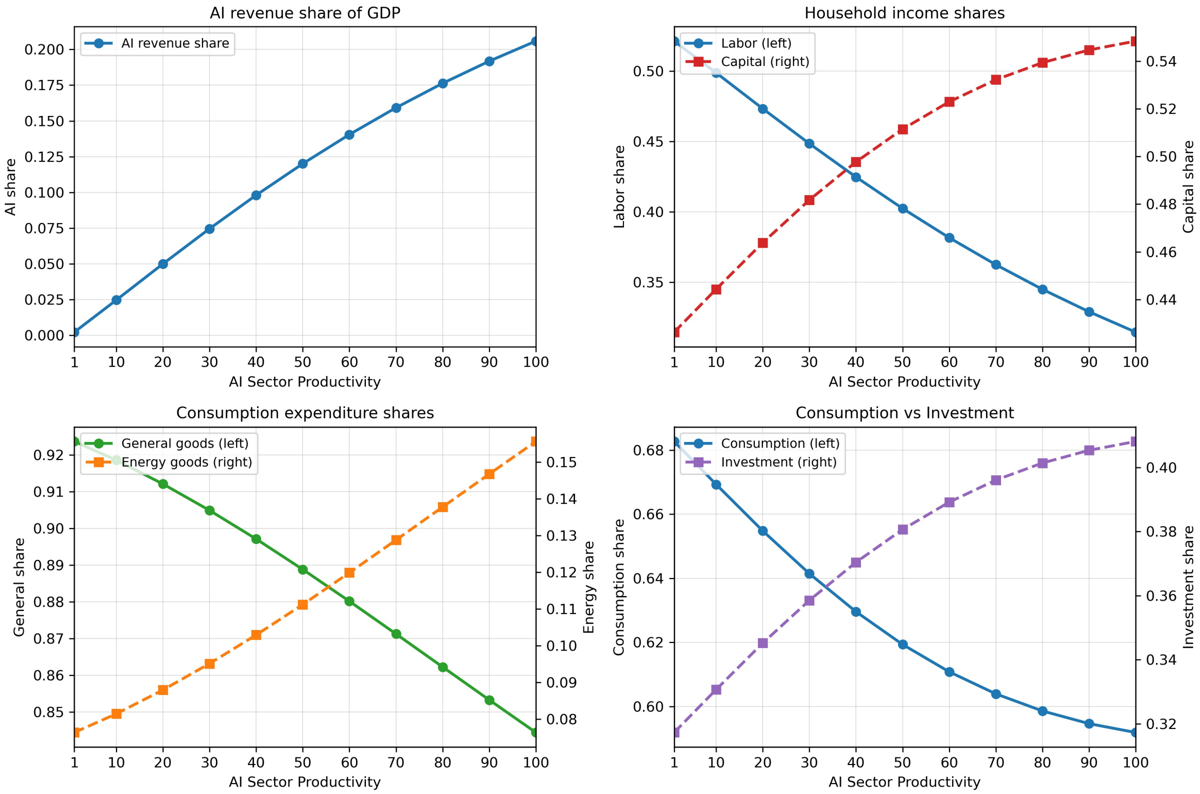

Figure 2: Shares in income and expenditure as AI productivity rises (levels).

Figure 2 highlights the shifts in income and expenditure shares. The AI revenue share of GDP expands as the sector grows. Concurrently, the economy transitions from a labor-intensive to an AI- and capital-intensive structure, leading to a decline in the labor income share and a rise in the capital income share. Reflecting the surge in energy prices, the household expenditure share on energy goods nearly doubles in the 100x productivity scenario.

5 Sensitivity: Labor-AI Substitution

We next analyze the sensitivity of our results to the elasticity of substitution (EoS) between labor and AI (σ_{inner}). We compare the baseline case ($\sigma_{inner} = 2.05$) with a "high substitution" scenario ($\sigma_{inner} = 2.15$), recalibrating the model for each case.

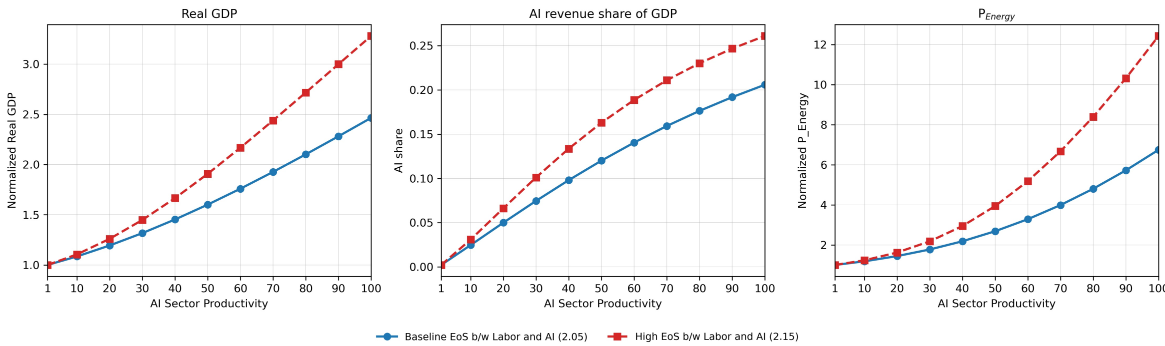

Figure 3: Sensitivity of Real GDP, AI share, and energy price to higher AI productivity under alternative labor-AI substitution elasticities.

Figure 3 reports the responses of Real GDP, the AI revenue share, and energy prices. The results demonstrate that macroeconomic outcomes are highly sensitive to the labor-AI elasticity. A modest increase in the elasticity (0.1 points) dramatically amplifies the effects of AI productivity growth. Most notably, the response of energy prices doubles in the high-substitution scenario. This implies that as labor and AI become more substitutable, the expansion of the AI sector accelerates, placing significantly greater pressure on energy markets.

6 Conclusion

This note has provided a quantitative assessment of the general equilibrium effects of AI development, with a specific focus on the trade-off between economic growth and energy constraints. By calibrating a three-sector dynamic model to the Japanese economy, we demonstrated that a 100 times increase in AI productivity corresponds to a 2.5 times expansion in Real GDP. However, this growth comes with significant structural shifts and costs. We highlighted that welfare gains are dampened by the high investment requirements of an AI-intensive steady state. Moreover, our results confirm the existence of a macroeconomic "Jevons paradox," where the surge in demand for AI services drives energy prices up by a factor of nearly seven. Finally, the sensitivity of our results to the labor-AI substitution elasticity underscores the uncertainty inherent in this transition. As AI technology continues to evolve, understanding the precise nature of factor substitution will be critical for predicting the magnitude of energy market pressures and labor share dynamics.

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