

Generative AI Meets Data Quality: Innovation or Risk?

Qing Chang¹ Danxia Xie¹ Longtian Zhang²

1. School of Social Sciences, Tsinghua University
2. School of International Trade and Economics, Central University of Finance and Economics

zhanglongtian@cufe.edu.cn

Seminar @ Beijing Institute of Mathematical Sciences and Applications

January 9, 2026

Outline

- 1 Introduction
- 2 The General Model
- 3 Balanced Growth Path
- 4 Numerical Examples and Further Discussions
- 5 Conclusion

Introduction

Motivating Facts

- In recent years, the significance of data has been widely acknowledged by both academia and industry.
 - Newly emerging industries leverage data as a key factor of production and innovation.
 - The rising of Generative AI, like ChatGPT and other LLMs, is reshaping various aspects of our lives by producing an increasing volume of contents.
- Bali (PNAS, 2024): Generative AI is reshaping the social sciences by streamlining routine research tasks.
 - Writing, data cleaning, and software programming.
- The performance and reliability of AI systems critically depend on the quality of the data they utilize.

Introduction

Motivating Facts (Cont.)

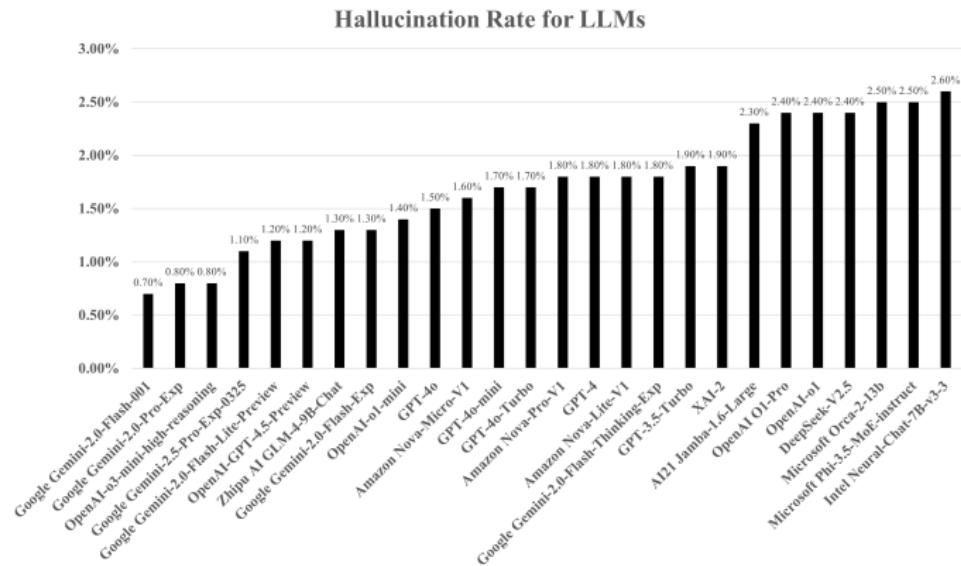


Figure: Hallucination Rate for Selected LLMs

This metric measures how frequently an LLM introduces hallucinations when summarizing a document.

Introduction

Overview

We propose a semi-endogenous growth model incorporating two types of data, each representing different levels of real-world information, and analyze the model's behavior with an emphasis on data quality.

- AI-generated data: derived from existing datasets, with labor introduced as the sole marginal input in the generation process.
- Data quality: determined by the ratio of the two types of data used and directly influences the error rate in production.
 - Higher data quality \Rightarrow lower error rate \Rightarrow higher total production
- Competitive equilibrium vs. social optimal

Introduction

Key Results

Producer data (real-world information) vs. AI-generated data

- Competitive equilibrium: firms may lose their business if their error rates become too high, which come from low data quality.
 - They still underutilize producer data.
- Number of AI firms
 - The optimal number of AI firms should always be ONE, while in competitive equilibrium, there may be multiple firms.
 - The equilibrium number of AI firms depends on the investment in these firms, the generation process of AI-generated data, and among others.

Introduction

Literature: Research on AI

- Potential risks of generative AI: Acemoglu and Lensman (2024), Jones (2024).
- Research in computer science: Shumailov et al. (2024), Wenger (2024).
- Economic research in AI: Acemoglu (2024), Korinek and Vipra (2024), Brynjolfsson et al. (2025).

Introduction

Literature: Data in Macro and Growth

- Different paths to the economics of data:
 - Jones and Tonetti (2020): Horizontal nonrivalry & production process;
 - Cong, Xie, and Zhang (2021): Dynamic nonrivalry & innovation process;
 - Cong, Wei, Xie, and Zhang (2022): Vertical nonrivalry & both production process and innovation process simultaneously;
 - Xie and Zhang (2023): “producer data” lead to higher growth rate than “consumer data.”
- Data do not always lead to sustained economic growth: Farboodi and Veldkamp (2020, 2021); Veldkamp (2023).

The General Model

Setup

- Representative household
 - consumption c_t , labor allocations $L_{i,t}$, $l_{P,t}$, $l_{A,t}$, and $l_{R,t}$.
- Final good producer
 - combine intermediate goods to produce output Y_t .
 - employ labor to generate producer data as byproduct
- Intermediate good producers
 - Use overall dataset and labor to produce intermediate goods.
- Generative AI firms
 - Generate data using the existing data and labor.
- Innovation sector
 - Use labor to innovate.

The General Model

Representative Consumers

Utility function:

$$U = \int_0^{\infty} e^{-(\rho-n)t} \ln c_t dt,$$

- Budget constraint:

$$\dot{a}_t = (r_t - n)a_t + w_t - c_t.$$

The General Model

Final good producer

- Two inputs (intermediate goods and labor) and two outputs (final good and producer data).
- Profit maximization problem:

$$\max_{\{Y_{i,t}, L_{P,t}\}} Y_t + p_{D_P,t} D_{P,t} - \int_0^{N_t} p_{i,t} Y_{i,t} di - w_t L_{P,t},$$

where,

$$D_{P,t} = \left(\frac{Y_t}{L_t} \right)^\theta L_{P,t}.$$

The General Model

Generative AI firms

- AI-generated data are produced by:

$$\dot{d}_{A,t} = \frac{\psi}{M} d_{A,t}^\zeta L_{A,t} - \delta_A d_{A,t}.$$

- There are $M > 0$ homogeneous Generative AI firms in the economy, each operates in a monopolistic environment.
- $d_{A,t}$ denotes the AI-generated data produced by a single firm.
- The aggregate AI-generated data is given by $D_{A,t} = M d_{A,t}$.
- The optimization problem:

$$\max_{\{D_{A,t}, L_{A,t}\}} \int_0^\infty \exp\left(-\int_0^t r_\tau d\tau\right) \left[p_{D_{A,t}}(d_{A,t}) \cdot d_{A,t} - w_t \frac{L_{A,t}}{M} \right] dt,$$

The General Model

Generative AI firms (Cont.)

- We assume that the AI firm must incur a substantial upfront investment before it can begin providing AI-generated data to other firms.
 - Emergent capabilities of AI: \mathcal{G} , which is viewed as a fixed cost.
 - \mathcal{G} is the threshold at which AI models become operational and begin generating new data.
 - Estimations: OpenAI's GPT-4 at \$40 million and Google's Gemini Ultra at \$30 million (Cottier et al., 2025).
- Free-entry condition of AI firms: The discounted profit of AI firms $\Pi = \mathcal{G}$.

The General Model

Intermediate good producers

- Combination of different types of data:

$$D_{i,t} = \left[\beta D_{P,i,t}^{\frac{\epsilon-1}{\epsilon}} + (1-\beta) D_{A,i,t}^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}},$$

- Error rate that AI-generated data making mistakes:

$$e_{i,t} = e_0 \cdot \exp(-\xi Q_{i,t}),$$

- Data quality:

$$Q_{i,t} = \left(\frac{D_{P,i,t}}{D_{A,i,t}} \right)^\tau,$$

- Production function:

$$Y_{i,t} = (1 - e_{i,t}) D_{i,t}^\eta L_{i,t}.$$

The General Model

Intermediate good producers (Cont.)

- Decision problem:

$$r_t V_{i,t} = \max_{\{L_{i,t}, D_{P,i,t}, D_{A,i,t}\}} Y_t^{\frac{1}{\sigma}} \left(1 + \theta p_{D_P,t} Y_t^{\theta-1} \frac{L_{P,t}}{L_t^\theta} \right) Y_{i,t}^{1-\frac{1}{\sigma}} - w_t L_{i,t} - p_{D_P,t}^d D_{P,i,t} - p_{D_A,t}^d D_{A,i,t} + \dot{V}_{i,t} - \delta(e_{i,t}) V_{i,t}.$$

- “Loss of business” effect $\delta(e_i, t)$: when an incumbent firm excessively relies on AI-generated data in production, leading to a high probability of errors, potential intermediate goods producers may have an opportunity to displace it.

The General Model

Data intermediary

- Two types of data intermediaries: one that handles producer data and another that handles AI-generated data.
- Both intermediaries operate as monopolists in their respective data markets but are constrained by free entry into data intermediation.
- One problem is:

$$\max_{p_{D_P,t}^d, D_{P,t}} p_{D_P,t}^d \int_0^{N_t} D_{P,i,t} di - p_{D_P,t} D_{P,t},$$

subject to

$$D_{P,i,t} \leq D_{P,t}.$$

The General Model

Innovation problem

- The innovation process is:

$$\dot{N}_t = \frac{1}{\chi} L_{R,t},$$

- Free entry condition:

$$\chi w_t = V_{i,t} + \frac{\int_0^{N_t} \delta(e_{i,t}) V_{i,t} di}{\dot{N}_t}.$$

Balanced Growth Path

Optimal Allocation

- Homogeneity among different varieties of intermediate goods:

$$D_{P,i,t} = D_{P,t}, \quad D_{A,i,t} = D_{A,t}, \quad e_{i,t} = e_t, \quad Q_{i,t} = Q_t$$

- Define a constant:

$$\mathcal{A} \equiv \frac{(1 - \zeta) [\rho + (1 - \zeta) \delta_A]}{n + \delta_A (1 - \zeta)},$$

Balanced Growth Path

Optimal Allocation

When Producer Data and AI-Generated Data Grow at Different Rates

The labor shares allocated to different sectors are given by:

$$l_P^{sp} \rightarrow \begin{cases} 0, & \text{if } \frac{\theta}{\sigma-1} + 1 < \frac{1-\theta\eta}{1-\zeta}, \\ \frac{\eta\rho(\sigma-1)}{n+\rho(1+\eta)(\sigma-1)}, & \text{if } \frac{\theta}{\sigma-1} + 1 > \frac{1-\theta\eta}{1-\zeta}, \end{cases}$$

$$l_A^{sp} \rightarrow \begin{cases} \frac{\eta\rho(\sigma-1)}{\mathcal{A}n + \rho(\sigma-1)(\mathcal{A} + \eta)}, & \text{if } \frac{\theta}{\sigma-1} + 1 < \frac{1-\theta\eta}{1-\zeta}, \\ 0, & \text{if } \frac{\theta}{\sigma-1} + 1 > \frac{1-\theta\eta}{1-\zeta}, \end{cases}$$

$$l_R^{sp} \rightarrow \begin{cases} \frac{\mathcal{A}n}{\mathcal{A}n + \rho(\sigma-1)(\mathcal{A} + \eta)}, & \text{if } \frac{\theta}{\sigma-1} + 1 < \frac{1-\theta\eta}{1-\zeta}, \\ \frac{n}{n+\rho(1+\eta)(\sigma-1)}, & \text{if } \frac{\theta}{\sigma-1} + 1 > \frac{1-\theta\eta}{1-\zeta}, \end{cases}$$

$$g_c^{sp} = g_y^{sp} = \begin{cases} \left(\frac{1}{\sigma-1} + \frac{\eta}{1-\zeta} \right) n, & \text{if } \frac{\theta}{\sigma-1} + 1 < \frac{1-\theta\eta}{1-\zeta}, \\ \frac{1}{1-\theta\eta} \left(\frac{1}{\sigma-1} + \eta \right) n, & \text{otherwise.} \end{cases}$$

Balanced Growth Path

Optimal Allocation (Cont.)

- Discussions.

- When AI-generated data dominate, I_P^{sp} shrinks to zero.
 - Although the error rate in intermediate goods production converges to one—resulting in a near-zero survival rate for the corresponding intermediate goods
 - the economy still grows at a positive rate due to the low cost and large volume of AI-generated data used in production.
- When producer data dominate, I_A^{sp} shrinks to zero.
 - The positive effect of AI-generated data is not large enough for usage in this case, while they still have negative effects.

Balanced Growth Path

Competitive equilibrium

Competitive Equilibrium

When $(1 - \tau)\epsilon > 1$, the labor shares allocated to different sectors converge to:

$$I_P^{dc} \rightarrow \begin{cases} 0, & \text{if } \frac{\theta}{\sigma - 1} + 1 < \frac{1 - \theta\eta}{1 - \zeta}, \\ \frac{C\eta}{C(1 + \eta) + n\chi}, & \text{if } \frac{\theta}{\sigma - 1} + 1 > \frac{1 - \theta\eta}{1 - \zeta}, \end{cases}$$
$$I_A^{dc} \rightarrow \begin{cases} \frac{C\eta^2}{C(\mathcal{A} + \eta^2) + n\chi\mathcal{A}}, & \text{if } \frac{\theta}{\sigma - 1} + 1 < \frac{1 - \theta\eta}{1 - \zeta}, \\ 0, & \text{if } \frac{\theta}{\sigma - 1} + 1 > \frac{1 - \theta\eta}{1 - \zeta}, \end{cases}$$
$$I_R^{dc} \rightarrow \begin{cases} \frac{n\chi\mathcal{A}}{C(\mathcal{A} + \eta^2) + n\chi\mathcal{A}}, & \text{if } \frac{\theta}{\sigma - 1} + 1 < \frac{1 - \theta\eta}{1 - \zeta}, \\ \frac{n\chi}{C(1 + \eta) + n\chi}, & \text{if } \frac{\theta}{\sigma - 1} + 1 > \frac{1 - \theta\eta}{1 - \zeta}. \end{cases}$$

Here, C is a constant which is defined by:

$$C \equiv \begin{cases} \frac{n\chi(\sigma - 1)(\rho + \delta_0 e_0^2)}{(n + \delta_0 e_0^2)(1 + \eta - \sigma\eta)}, & \text{if } \frac{\theta}{\sigma - 1} + 1 < \frac{1 - \theta\eta}{1 - \zeta}, \\ \frac{\chi\rho(\sigma - 1)}{1 + \eta - \sigma\eta}, & \text{if } \frac{\theta}{\sigma - 1} + 1 > \frac{1 - \theta\eta}{1 - \zeta}. \end{cases}$$

The growth rate of the economy remaining identical to that in the optimal allocations.

Balanced Growth Path

Competitive Equilibrium (Cont.)

- I_P^{dc} shrinks to zero when AI-generated data dominate, while I_A^{dc} shrinks to zero when producer data dominate.
- “Loss of business” effect
 - negligible when $g_{D_A}^{dc} \leq g_{D_P}^{dc}$
 - significant when $g_{D_A}^{dc} > g_{D_P}^{dc}$, but does not change the trend that $I_{P,t} \rightarrow 0$ (the producer data sector is still negligible).
- An important condition that ensures the model is well-behaved:

$$(1 - \tau)\epsilon > 1$$

- the sensitivity of data quality should not be excessively large
- the elasticity of substitution between the two types of data should not be too low

Balanced Growth Path

Data quality

- The growth rates of data quality are also different in the two scenarios.

$$\bar{Q}_t^{sp} \propto \begin{cases} L_t^{\tau \left(1 + \frac{\theta}{\sigma-1} - \frac{1-\theta\eta}{1-\zeta} \right)}, & \text{if } \frac{\theta}{\sigma-1} + 1 \leq \frac{1-\theta\eta}{1-\zeta}, \\ L_t^{\eta \left[1 + \frac{\theta}{1-\theta\eta} \left(\frac{1}{\sigma-1} + \eta \right) \right]}, & \text{if } \frac{\tau-\eta}{\tau} \left(\frac{\theta}{\sigma-1} + 1 \right) < \frac{1-\theta\eta}{1-\zeta} < \frac{\theta}{\sigma-1} + 1, \\ L_t^{\tau \left[\frac{1}{1-\theta\eta} \left(\frac{\theta}{\sigma-1} + 1 \right) - \frac{1}{1-\zeta} \right]}, & \text{if } \frac{\tau-\eta}{\tau} \left(\frac{\theta}{\sigma-1} + 1 \right) \geq \frac{1-\theta\eta}{1-\zeta} \end{cases}$$

and

$$\bar{Q}_t^{dc} \propto \begin{cases} L_t^{\frac{\tau}{1-\tau} \left(\frac{\theta}{\sigma-1} - \frac{1-\theta\eta}{1-\zeta} + 1 \right)}, & \text{if } \frac{\theta}{\sigma-1} + 1 < \frac{1-\theta\eta}{1-\zeta}, \\ L_t^{\frac{\tau}{\zeta\epsilon-1} \left[\frac{\epsilon(\zeta-1)}{1-\theta\eta} \left(\frac{\theta}{\sigma-1} + 1 \right) + \epsilon \right]}, & \text{if } \frac{\theta}{\sigma-1} + 1 \geq \frac{1-\theta\eta}{1-\zeta} \quad \text{and} \quad \zeta\epsilon < 1, \\ L_t^{\tau \left[\frac{1}{1-\theta\eta} \left(\frac{\theta}{\sigma-1} + 1 \right) - \frac{1}{1-\zeta} \right]}, & \text{if } \frac{\theta}{\sigma-1} + 1 \geq \frac{1-\theta\eta}{1-\zeta} \quad \text{and} \quad \zeta\epsilon \geq 1. \end{cases}$$

Balanced Growth Path

Number of Generative AI Firms

Number of Generative AI Firms

When $g_{D_A} \geq g_{D_P}$ —indicating that AI-generated data dominate the economy—along a balanced growth path, the optimal number of Generative AI firms is **ONE**, regardless of the magnitude of emergent capabilities \mathcal{G} . In contrast, under the competitive equilibrium, this number converges to:

$$M^{dc} = \left\{ \frac{(\mathcal{A} - \eta)(\sigma - 1)(1 - \epsilon_0)}{\sigma\eta(\rho - n)(n\chi)^{\frac{1}{\sigma-1}}\mathcal{G}} \left[\frac{\psi(1 - \zeta)}{n + \delta_A(1 - \zeta)} \right]^{\frac{\eta}{1-\zeta}} (I_R^{dc})^{\frac{1}{\sigma-1}} (I_A^{dc})^{1 + \frac{\eta}{1-\zeta}} L_0^{1 + \frac{1}{\sigma-1} + \frac{\eta}{1-\zeta}} \right\}^{\frac{1-\zeta}{1-\zeta(1-\eta)}}.$$

Numerical Examples and Further Discussions

Calibration

Parameters	Meaning	Value	Comment
ρ	Subjective discount rate	0.03	Standard
n	Population growth rate	0.02	Standard
σ	Elasticity of substitution (goods)	4	Standard
χ	Labor cost of entry	0.01	Standard
η	Importance of data in production	0.06	Jones & Tonetti (2020)
δ_A	Depreciation rate of AI-generated data	0.2	Estimated
ζ	Contribution of existing AI-generated data	0.25	Estimated
θ	Importance of output in producer data generation	0.81	Calculated from model
ψ	Efficiency term in AI-generated data generation	1	Normalized
ϵ	Elasticity of substitution (data)	50	Discretionary
e_0	Basic error rate	0.95	Discretionary
β	Share of producer data in overall dataset	0.5	Normalized
ξ	Sensitivity of data quality to error rate	1	Normalized
τ	Elasticity of data ratio to data quality	0.5	To be discussed
κ	Weight on data quality versus consumption	0.10	To be discussed
δ_0	"Loss of business" effect	0.4	To be discussed

Numerical Examples and Further Discussions

Numerical Examples When $g_{D_A} \neq g_{D_P}$

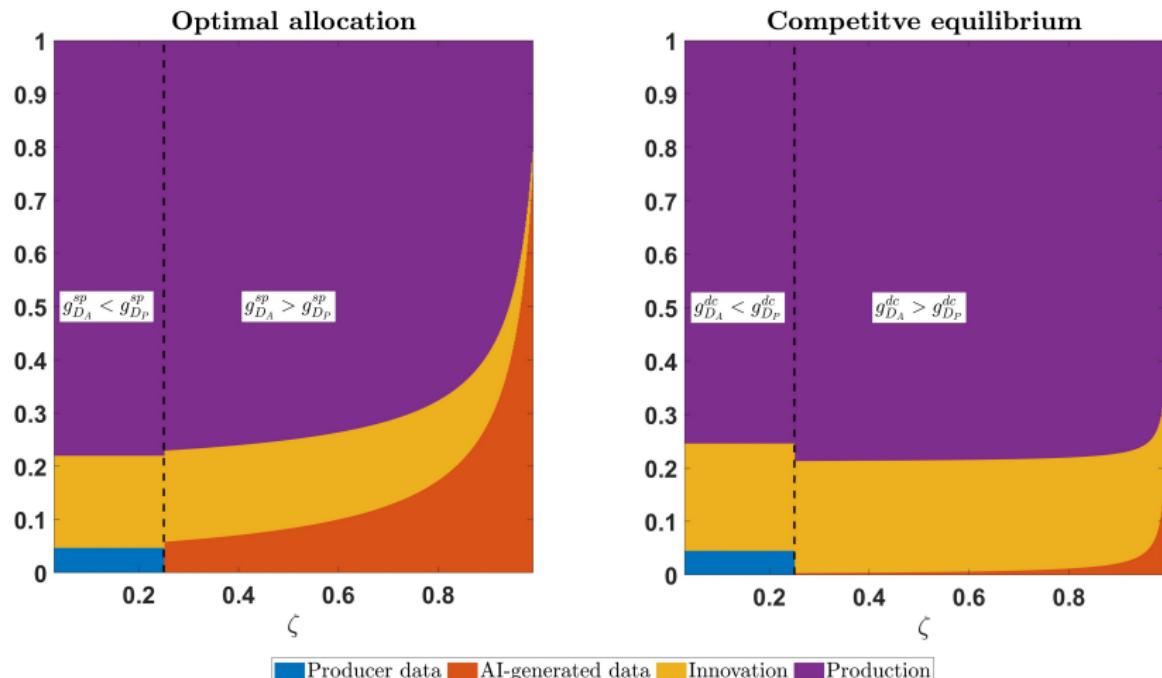


Figure: Labor allocations in the four different sectors

Numerical Examples and Further Discussions

Numerical Examples When $g_{D_A} \neq g_{D_P}$ (Cont.)

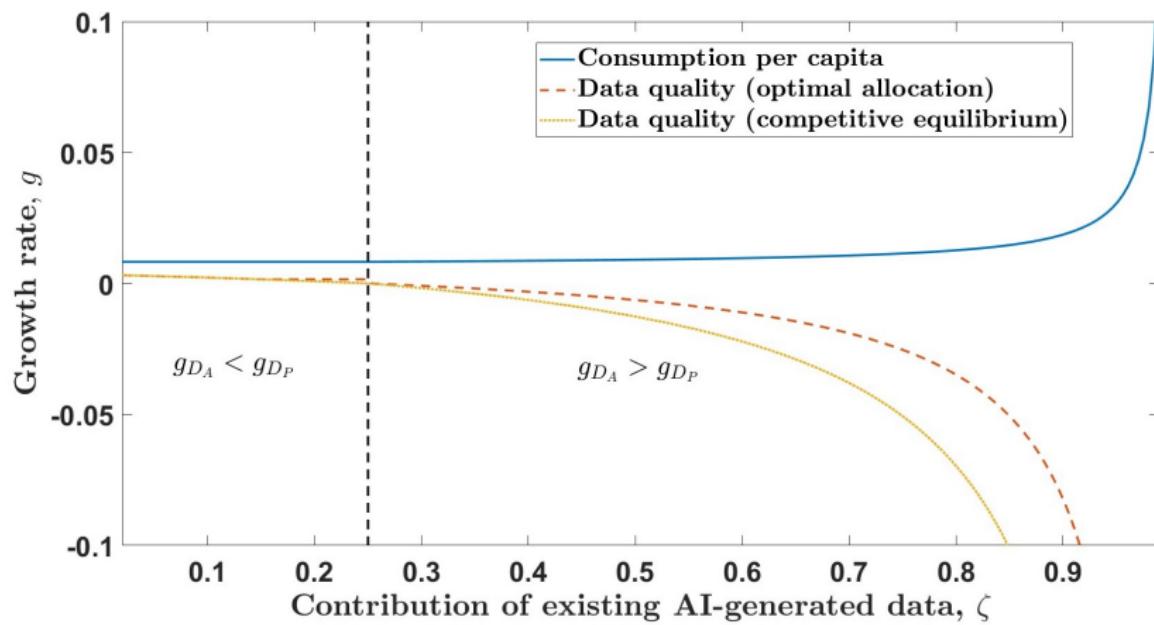


Figure: Growth rates of consumption per capita and data quality

Numerical Examples and Further Discussions

Number of Generative AI Firms

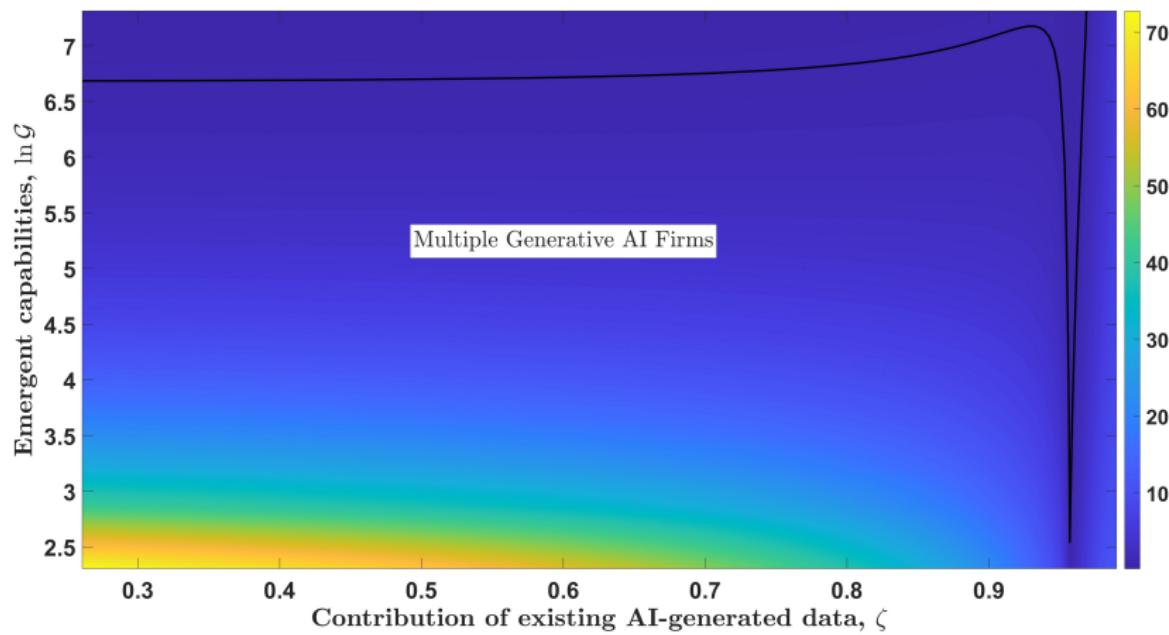


Figure: Number of Generative AI firms in Competitive Equilibrium

Numerical Examples and Further Discussions

Policy implications

- Although AI-generated data serve as a powerful substitute for conventional data in many fields of production, we must remain cautious about the dystopian aspects of their widespread use.
 - Encourage better data composition: subsidies for high-quality producer data; limiting excessive entry in the AI sectors.
 - Support public data infrastructure that can improve baseline quality of data.
- In most cases, there are too many Generative AI firms in the market.
 - Multiple firms leads to redundant investment.
 - Governments need not be overly concerned about the concentration trend in the AI industry.

Conclusion

- We develop an endogenous growth model that incorporates AI-generated data from the perspective of data quality to highlight the potential risks of production errors arising from the widespread use of Generative AI.
 - We emphasize the importance of integrating real-world data, such as the producer data considered in our model.
 - Firms consistently underuse real-world data.
- This finding raises important policy considerations regarding whether governments should regulate the use of AI-generated data and the broader development of the AI industry.
 - Our study contributes to the literature by advancing growth theory on risks associated with AI technologies and data as a factor of production.

Thanks for your attention!