Is Generative AI Old Wine in a New Bottle? An Asset Pricing Model on Generative AI and Data Economy

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Abstract

We build a two-sector production-based asset pricing model in which the AI sector provides computation to the general goods sector. The general goods sector applies computation on data to create an AI agent that is a substitute for human labor. Data are a by-product of general goods production and are owned by the general goods sector. Our model shows that the progress of AI, in the form of an increase of productivity or elasticity of substitution (EIS), drives up the production, profit, and the participant of AI agent in economy. However, the increase in EIS drives up the demand for AI computation and drives down the labor demand, while the increase of AI productivity drives up the supply of AI computation and drives down the labor supply. Positive technological shocks depress the sector valuations of two sectors, while driving up wages. In addition, these shocks crowd out data-related investments in the general goods sector. Our model rationalizes recent empirical findings linking AI development, data economies, and labor market outcomes and provides new insights into the implications of "DeepSeek shocks", episodes of sudden productivity leaps driven by algorithmic breakthroughs.

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I. Introduction

Artificial intelligence (AI) exerts a significantly greater influence on labor markets and data utilization compared to past industrial revolutions. In the labor market, the rapid expansion of the AI sector has driven significant labor reallocation towards activities focused on training, labeling, validating, and maintaining AI systems. In addition, general-purpose AI agents increasingly substitute human labor, marking a notable shift from earlier technologies that primarily complemented human efforts. In terms of data usage, AI's performance heavily relies on continuous access to high-quality, specialized data. Consequently, acquiring appropriate datasets and developing expertise in fine-tuning or prompt engineering have become critical for achieving effective and productive outcomes with the AI algorithm.

We develop a model to study how generative AI affects production, labor allocation, and asset valuation in the economy. In the static framework, both the general goods sector and the AI computation sector operate under Cobb-Douglas production technologies using capital and labor as inputs. In addition to hiring human labor, firms in the general goods sector purchase AI computation services from the AI sector and apply them to their proprietary data to create AI agents, which act as partial substitutes for labor. Labor is freely mobile across the two sectors, allowing endogenous reallocation in response to changes in technology and prices. On the dynamic side, the model features endogenous investment in both capital and data, capturing the feedback loop between data accumulation and AI productivity. The value of each sector and the allocation of resources are jointly determined by solving a social planner problem, which internalizes the dynamic externalities associated with the use of data and the development of AI.

We consider two types of AI progress. One is the increase in productivity, which means that the AI sector could produce the same quality and the same quantity of computation. Another is the increase in elasticity of substitution (EIS) between labor and the AI agent, which means that the AI agent performs better in various tasks in production activities. Both drive up the participant of AI agent in economy and then drive up production and profit. However, two types of AI advances have different impacts on labor and computation markets. The increase in EIS drives the demand for AI computation and drives the demand for labor. As a consequence, the wage and the amount of labor in the work decrease. In contrast, the increase of AI productivity drives the supply of AI computations up, which causes the price of AI computation to go down, and the wage to rise.

Our dynamic model illustrates that positive technological shocks depress the sector valuations of two sectors. This implication aligns with the intricate impact of "DeepSeek shocks", major algorithmic breakthroughs that drastically lower AI training costs. Although these improvements seem unequivocally beneficial to AI-sector firms, a striking, counterintuitive result emerges: intensified competition may drive down long-term profitability, ultimately reducing AI-sector valuations. In contrast, because the general goods sector is only indirectly exposed to AI disruptions, it experiences comparatively moderate declines in the sector value. As AI training costs fall, labor flows to the expanding AI sector, driving wages persistently above baseline levels. In addition, incremental gains in AI efficiency can stifle demand for structured data and crowd out data-related investments in the general goods sector.

The implications of our model align with recent empirical findings in the labor market. Acemoglu et al. (2022) observe that establishments adopting AI technologies tend to reduce hiring in non-AI roles while increasing recruitment for AI-specific positions, indicating a shift in labor demand. This substitution effect between AI agents and human labor is further supported by studies such as Hartley et al. (2024) and Eisfeldt et al. (2023) , which analyze the impact on the labor market of generative AI and Auer et al. (2024), which explore the role of AI in substituting human labor in various occupations. Furthermore, Hartley et al. (2024) showed that LinkedIn data reveal a significant increase in employment within AI-focused companies such as OpenAI, Anthropic, and Google DeepMind. In contrast, firms in the general goods sector are reducing the hiring of roles that can be replaced by AI agents, as documented by Hui et al. (2024).

Our integrated perspective on data and generative AI is informed by recent empirical findings that offer novel insights into the data economy. Eisfeldt et al. (2023) found that firms with greater exposure to AI technologies often possess substantial data assets, and this combination significantly explained abnormal stock returns following the release of GPT-3.5. Our framework provides an alternative interpretation of empirical results concerning the data economy. For instance, the higher premiums associated with a greater proportion of data scientists within firms, as documented by Corhay et al. (2023), can be attributed to increased exposure to productivity risks in the AI sector when a firm holds extensive data assets.

Data are becoming a standard input in a production function. For example, studies by Cong et al. (2021), Cong et al. (2022), Chang et al. (2023), and Chang et al. (2024)

explored various dimensions of how data contribute to production processes. Jones and Tonetti (2020) highlighted the non-rivalry nature of data in production separating them from traditional inputs like labor and capital. Farboodi and Veldkamp (2021) presented a framework in which data, generated through transactions, serve as an intangible asset that influences firm productivity and economic growth.

Our work builds on a growing body of research investigating how artificial intelligence (AI) transforms firms, industries, and economies through multiple channels, from shifts in knowledge production to changes in labor markets and strategic decision-making. A foundational contribution by Abis and Veldkamp (2024) examines how the economics of knowledge production evolves in the face of accelerating technological innovation, emphasizing the increasingly central role of AI in shaping research and development dynamics. Complementing this perspective, Babina et al. (2024) document a strong association between AI adoption and firm-level growth and innovation outcomes, while earlier work by Babina et al. (2022) reveals how the composition of the workforce adjusts in response to AI-driven transformations, highlighting the reallocation of human capital within firms. In terms of financial markets, Eisfeldt et al. (2023) provides novel evidence on the implications of generative AI valuation, showing how frontier technologies can shape corporate strategies and influence asset prices. From a theoretical point of view, Farboodi and Veldkamp (2021) develop a data economy model to explore the dynamic interaction between data availability, insight generation, and market growth. Building on the literature on technological diffusion, Zhang (2024b) extend the model of Pástor and Veronesi (2009) by incorporating habit formation into AI adoption decisions, offering a framework for understanding heterogeneity in adoption patterns. Relatedly, Jones (2024) examines how these adoption dynamics feed into broader macroeconomic and asset pricing implications, particularly in the context of a rapidly digitizing economy. At the societal level, recent work grapples with the uncertainty and risks posed by rapid technological change. Jones (2024) explores the tension between AI-driven economic acceleration and the possibility of catastrophic outcomes, a concern echoed in Chow et al. (2024), who link existential risks to changes in long-term real interest rates. Meanwhile, Zhang (2024a) highlights the unequal access to data and AI technologies as a source of long-term inefficiency and social cost, calling for well-designed regulatory interventions to ensure inclusive and sustainable innovation. Collectively, these studies underscore both the transformative potential of AI and the profound economic, organizational, and social challenges it presents. Realizing the full value of AI will require not only continued innovation, but also informed policy design, robust regulatory frameworks, and strategic investments aimed at managing risk and ensuring broad-based benefits.

In sum, this paper develops the first theoretical model that explains how generative AI affects the economy. In addition to capturing empirical results, we give a prediction of how the economy will behave with future AI advances. Conceptually, it extends the 'data economy' framework of Farboodi and Veldkamp (2021) by treating AI computation and data as integrated inputs, and broadens Hansen et al. (2024) endogenous production-based asset pricing. The predictions of the model are aligned with recent empirical findings and yield novel testable implications for future research. A natural direction for further theoretical work is to introduce heterogeneous firms within each sector.

II. Generative AI in Economy

Generative AI agent is an autonomous AI-driven system that perceives its environment, makes decisions, and executes actions to achieve specified goals with minimal human intervention, leveraging underlying generative AI models to enable flexible general-purpose reasoning and behavior. Two features distinguish generative AI: general purpose nature and autonomy. On the one hand, general purpose means that generative AI can possess a wider range of capabilities than traditional prediction-based models, challenging economic frameworks that view AI primarily as a tool for improve prediction accuracy (Baley and Veldkamp (2025)). This general-purpose capacity also means that generative AI needs task-specific data and information to function effectively in specific real-world production tasks. On the other hand, Its autonomy allows it to learn from past experience ('learning by doing'), utilize external tools to broaden its functionality, and design plans for achieve goals with minimal human guidance. Those capabilities have traditionally been seen as unique human skills. Now that generative AI can replicate these processes, it can serve as a closer substitute for human labor in tasks that require creativity, reasoning, and adaptability.

Generative AI represents a distinct sector that provides advanced AI computations to the broader economy. AI companies (e.g. NVIDIA, OpenAI) specialize in building, training, and refining large-scale models, then providing access to their computing power and AI services to general goods firms. Because developing these models requires substantial resources, such as massive GPU infrastructure, expert knowledge, and high-quality datasets, most general goods firms find it prohibitively expensive to handle in-house. In contrast, before the rise of large language models (LLMs), machine learning algorithms were largely open source, and the requirements for compute and data were modest enough that individual firms could train or fine-tune models internally. The algorithms or the necessary human capital were owned outright by the general goods firms, which form part of their intangible assets. Now, the shift toward complex, resource-intensive models has positioned specialized AI firms as key external providers of these capabilities.

A concise example can be seen in customer support: a firm can outsource its AI needs to a provider like OpenAI, paying for usage (e.g. per token) rather than investing in costly, large-scale model development. The firm supplies its proprietary data, such as product details and policy documents, which the AI uses to generate customer-tailored responses. Operating with minimal human oversight, the system autonomously retrieves relevant information, creates explanations, and solves issues, effectively replicating the role of a service agent. This real-world application illustrates how the general-purpose reach and independent operation of generative AI are reshaping production processes and labor dynamics in industries.

We make two main assumptions about generative AI in our production economy: (1) the AI sector is a separate sector; (2) the AI agent is the substitute of human labor. Symbolically, we model the labor input of the general goods sector as a composite of real human labor (L_g) and Artificial Intelligence agent ($\mathbb{L}$),

$$\mathbf{L} = \left[\iota \left(L_g\right)^{\gamma} + (1-\iota)\left(\mathbb{L}\right)^{\gamma}\right]^{\frac{1-\beta}{\gamma}},$$

, where AI agent $\mathbb{L}$ is formed by combining data (D) from general goods sector and AI computation (X) from AI sector:

$$\mathbb{L} = D^{\theta} X^{1-\theta}.$$

Data D are defined as the stock of data-related investments that enable firms to take advantage of Generative AI computation. This includes not only structured datasets, but also the data scientists who manage them and the hardware required to store and process them. Following Farboodi and Veldkamp (2021), we treat the data as the by-product of production owned by producers of general goods and employed in the production of consumption goods. While they conceptualizes data as "fuel" for predictive AI tasks, we explicitly incorporate data into the production function by combining data with AI computation as AI agent substituting human labor to capture the general purpose feature.

The labor should be understood as less knowledgeable or lower skilled workers that do not need a long time training to be functional in production. The evolution of knowledgeable labor is more like capital which has adjustment cost and depreciation. In our economy, we incorporate the knowledgeable labor as human capital into the capital K_a and K_g. Especially, we separate knowledgeable workers dealing with the adoption of AI in the general goods sector from capital K_g as the data D to investigate and highlight the data in the AI economy.

III. Static AI Economy Model

In this section, we build a static equilibrium model to investigate the impact of AI on labor and production under equilibrium conditions.

III.a. Economy Settings

Consider an economy composed of two production sectors: the AI sector (a) and the general goods sector (g). Each sector utilizes labor and capital, with fixed capital stocks for static analysis. Labor is frictionlessly allocated between sectors, with L_a representing labor in the AI sector and L_g in the general goods sector. The AI sector produces computations using capital K_a and labor L_a following the production function:

$$X = ZK_a^{\alpha} L_a^{1-\alpha},$$

where Z is the productivity of the AI sector. The general goods sector purchases the computations at a price p and uses them with the data D to build the AI agent $\mathbb{L}$ that is a substitute for labor. The AI agent is modeled as the combination of data and computations:

$$\mathbb{L} = D^{\theta} X^{1-\theta},$$

where D is the structured data that can be used in AI computing.

The general goods sector produces consumption goods Y using both human labor and the AI agent as substitutable inputs. The Labor input of general production should be a composite of real human labor and artificial labor:

$$\mathbf{L} = [\iota L_g^{\gamma} + (1-\iota)\mathbb{L}^{\gamma}]^{\frac{1}{\gamma}},$$

where ι determines the relative weight of traditional labor versus AI-based labor. The production function is given by:

$$Y = AK_g^{\beta}\mathbf{L}^{1-\beta}.$$

The profits for the general goods sector and the AI sector are:

$$\Pi_g = Y - wL_g - pX, \tag{1}$$

$$\Pi_a = pX - wL_a. \tag{2}$$

In equilibrium, both the labor market and the AI computation market are clearing. Two sectors maximize both profits and solve for optimal labor, computation allocations, and productions. The price of AI computation is denoted as p, and the competitive wage is denoted as w. The labor market is assumed to be frictionless, ensuring that the marginal product of labor is equalized across both sectors. The first order conditions are

General Goods Sector (FOC for L_g)

$$\frac{\partial \Pi_g}{\partial L_g} = Y \cdot (1-\beta)\iota \left(\frac{L_g}{\mathbf{L}}\right)^{\gamma} L_g^{-1} - w = 0.$$

The total wage wL_g paid to the labor is a $(1-\beta)\iota\left(\frac{L_g}{\mathbf{L}}\right)^{\gamma}$ portion of the total production Y in the general goods sector.

General Goods Sector (FOC for Computation X to determine p)

$$\frac{\partial \Pi_g}{\partial X} = Y \cdot (1-\beta)(1-\iota)(1-\theta)\left(\frac{\mathbb{L}}{\mathbf{L}}\right)^{\gamma} X^{-1} - p = 0.$$

The total computation payment pX paid to the AI sector is $(1-\beta)(1-\iota)(1-\theta)\left(\frac{\mathbb{L}}{\mathbf{L}}\right)^{\gamma}$ a portion of total production Y in the general goods sector.

AI Sector (FOC for L_a)

$$\frac{\partial \Pi_a}{\partial L_a} = (1-\alpha)pXL_a^{-1} - w = 0.$$

The total wage wL_a paid to the labor is $(1-\alpha)$ a portion of the computation revenue pX in the AI sector.

Household Optimization We follows the settings of labor suggested by Papanikolaou (2011). The total labor supply is normalized to unity and is distributed between these sectors and leisure (N):

$$1 = L_a + L_g + N.$$

We assume that labor is frictionlessly allocated to two sectors and leisure time. Households derive utility from consumption and leisure, with the utility function:

$$V = \log(CN^{\psi}),$$

where all production is used for consumption. The optimal trade-off between labor and leisure is determined by equating the marginal utility of leisure (in terms of consumption) to the marginal utility of consumption, leading to:

$$\frac{1}{w}\frac{\partial V}{\partial N} = \frac{\partial V}{\partial C}.$$

This condition implies that the labor supply satisfies:

$$N = \psi \frac{C}{w}.$$

Prices of Capital and Data The shadow prices of capitals and data are given by the derivative of profits. In essence, the shadow price of a factor measures how much the firm's profit would increase if that factor were marginally higher while keeping everything else constant. We denote these shadow prices by V_{K_g} for the capital of general goods, V_{K_a} for the capital of the AI sector, and V_D for data.

$$V_{K_g} = \frac{\partial \Pi_g}{\partial K_g} = \beta \frac{Y}{K_g}, \tag{3}$$

$$V_{K_a} = \frac{\partial \Pi_a}{\partial K_a} = \alpha \frac{pX}{K_a} = \alpha(1-\beta)(1-\iota)(1-\theta)\left(\frac{\mathbb{L}}{\mathbf{L}}\right)^{\gamma} \frac{Y}{K_a} \tag{4}$$

$$V_D = \frac{\partial \Pi_g}{\partial D} = (1-\beta)(1-\iota)\theta \left(\frac{\mathbb{L}}{\mathbf{L}}\right)^{\gamma} \frac{Y}{D} \tag{5}$$

These results collectively show that the shadow price of each factor increases when it is used more intensively when the corresponding share parameter (e.g. β, α, or θ) is larger. If, in a dynamic model, K_g, K_a, and D accumulate over time, the planner or the firms would tend to invest more in whichever factor has the highest shadow price. For example, if $1-\iota$ is large, then the marginal values of K_a and D become higher, providing incentives to investment in the AI sector. The term $\left(\frac{\mathbb{L}}{\mathbf{L}}\right)^{\gamma}$ captures how intensively AI-labor is being used relative to total labor (including human labor). As AI becomes more prevalent, namely $\mathbb{L}$ increases relative to $\mathbf{L}$, the marginal products of AI-related factors K_a and D increase.

The three shadow prices $\left(V_{K_g}, V_{K_a}, V_D\right)$ reflect the instantaneous marginal value of each fixed factor in the production of final consumption goods. If these factors could be reallocated or accumulated, their equilibrium levels would increase to equalize these marginal values (up to costs), leading to stable ratios among K_g, K_a, and D in the long run. If the number of one factor, say D, is below the stable number, the price V_D would be higher than others and planners would invest more in data. These intuitions are also shown in the dynamic model.

III.b. Model Results

In this section, we examine the effects of AI progress on the economy in equilibrium by considering two key developments. First, as AI agents become increasingly intelligent, the elasticity of substitution, $\frac{1}{1-\gamma}$, between traditional labor in the general goods sector (L_g) and AI agents ($\mathbb{L}$) increases. Second, improvements in the efficiency and productivity of the AI sector, indicated by Z, allow it to deliver the same level of computational output while using less capital and labor. Moreover, we investigate the adoption of AI within the general goods sector, where such adoption is quantified by the amount of data available for AI computing, represented by D. Consequently, we characterize the equilibrium conditions as functions of the parameters γ, Z, and D. An alternative to thinking about AI progress is the increase in the intensity of the AI agent of production $1-\iota$, which is the way economic historians think about the Industrial Revolution as an increase in the capital intensity of production.

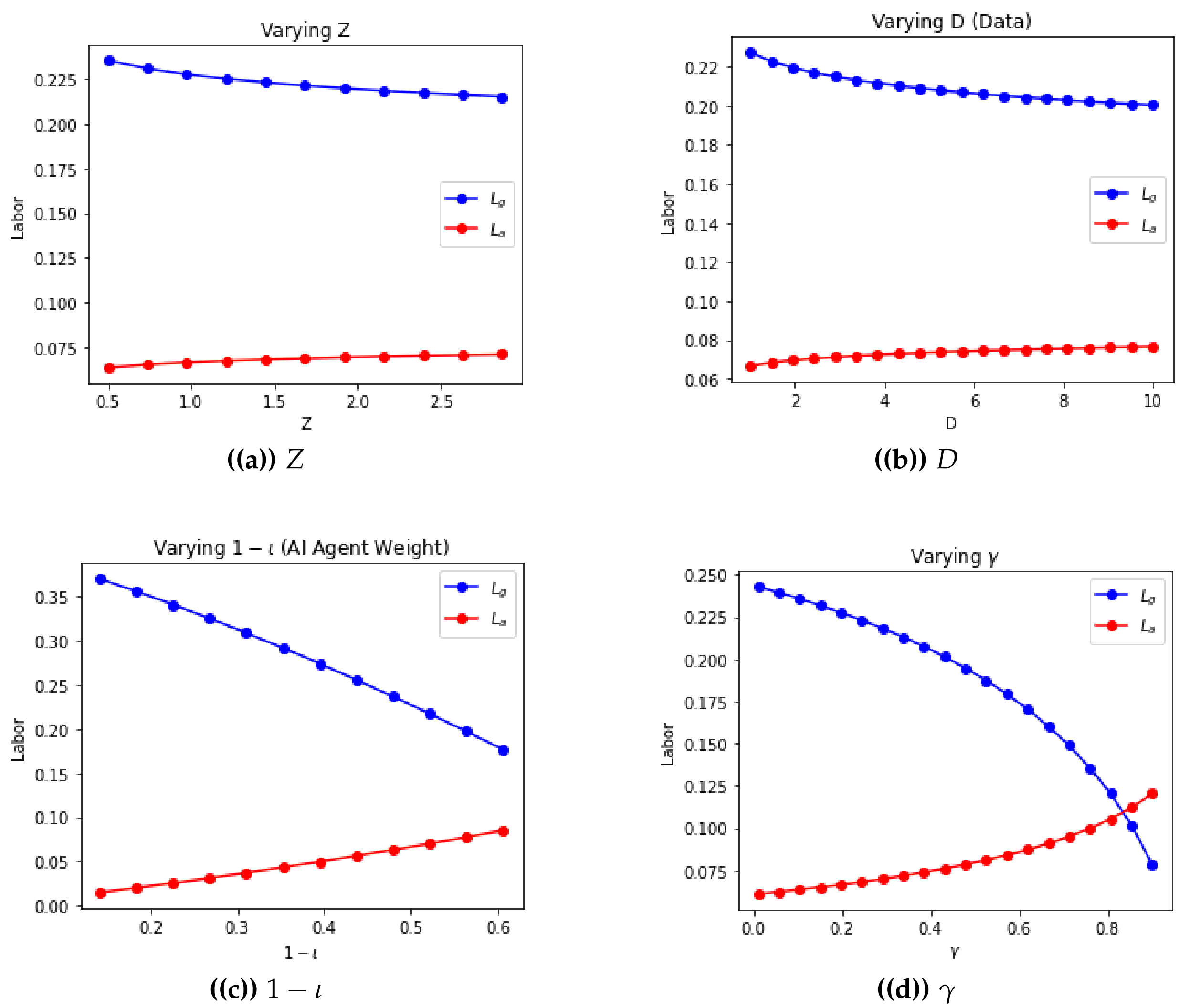
In the following results, we focus on a calibration in which the simulation parameters are given by

$$\alpha = 0.5, \quad \gamma = 0.1, \quad \iota = 0.5, \quad \beta = 0.3, \quad \theta = 0.5, \quad \psi = 1$$

which are 'safe' guesses in the absence of direct estimations. We set the initial capitals, data and productivity to be

$$K_g = 4, \quad K_a = 1, \quad D = 1, \quad A = 0.1, \quad Z = 1.$$

The productivity of the AI sector is much higher than that of the general goods sector to show the scalability of AI computation.

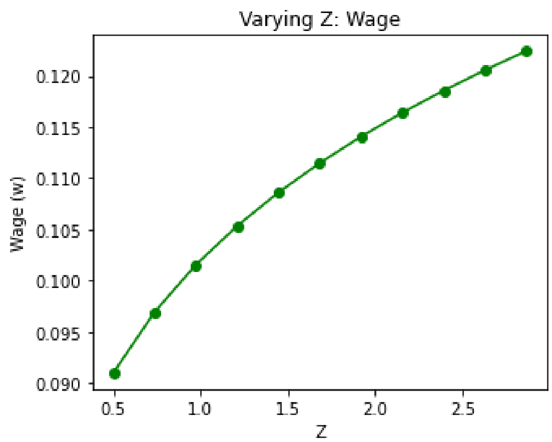


((a)) Z **((b))** D **((c))** $1-\iota$ **((d))** γ

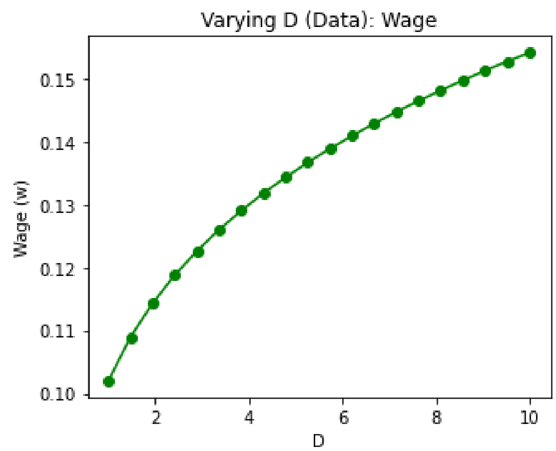
Figure III.1: AI Impact on Labor Market

Analysis of Figure Varying γ (Elasticity of substitution)

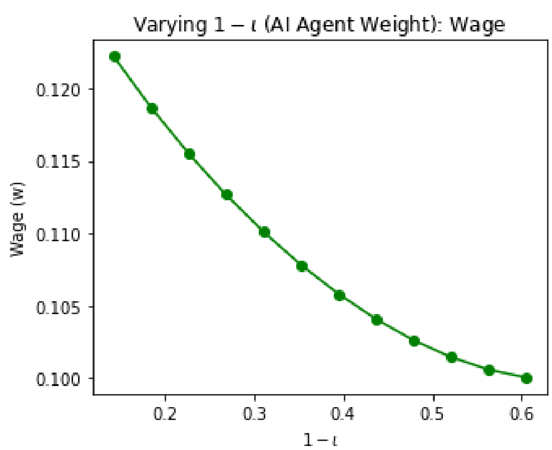
We explain the empirical findings regarding the release of GPT-3.5 by highlighting changes in γ, which measures the extent to which AI agents can replace human workers. In line with Eisfeldt et al. (2023), who document that firms with greater exposure to Generative AI exhibit higher abnormal returns and profits following GPT's release—and that occupations more exposed to Generative AI see fewer job postings and lower



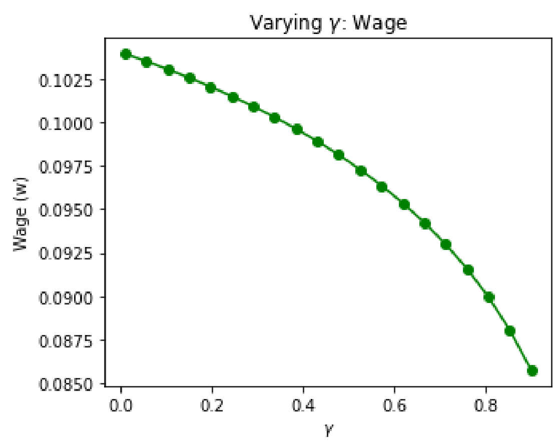
((a)) Z



((b)) D

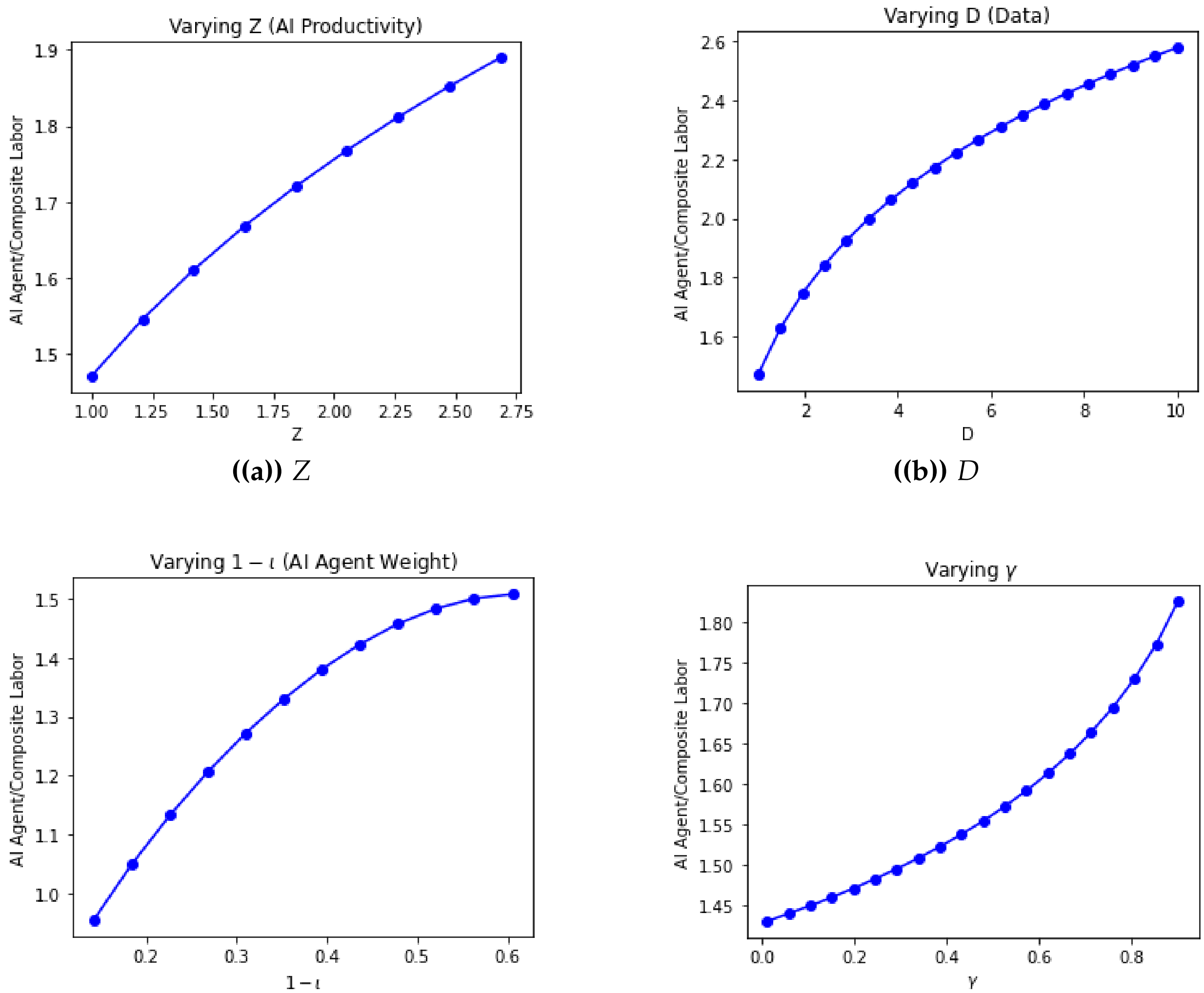


((c)) $1 - \iota$



((d)) γ

Figure III.2: AI Impact On Wage



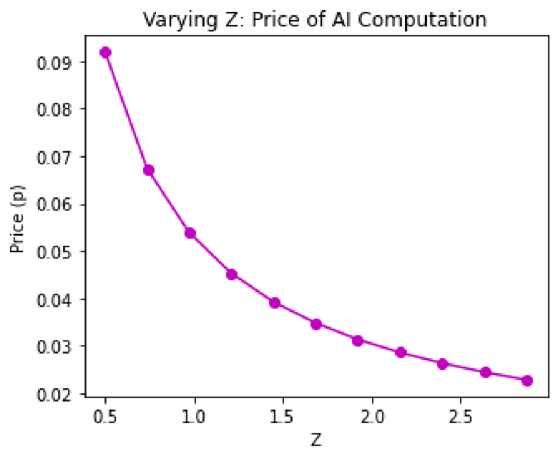
((a)) Z

((b)) D

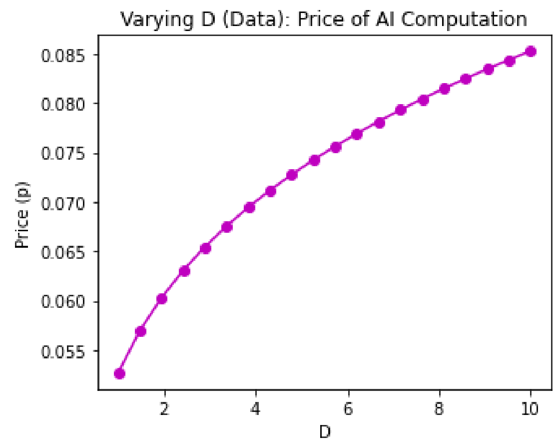
((c)) $1-\iota$

((d)) γ

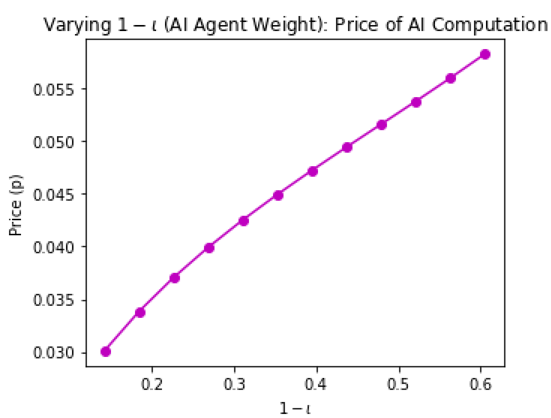
Figure III.3: AI Impact On labor composite



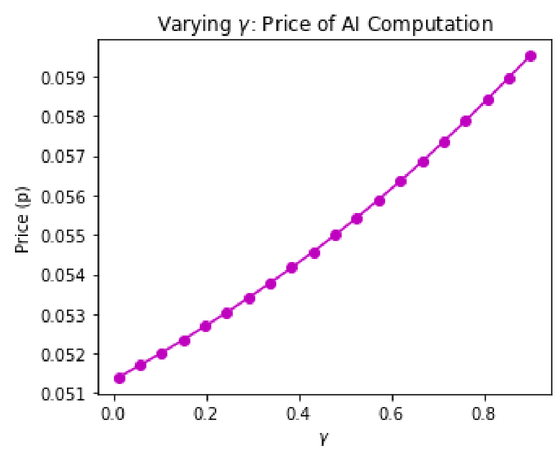
((a)) Z



((b)) D

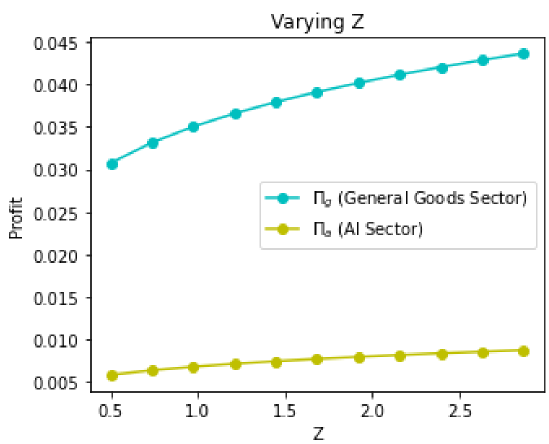


((c)) $1 - \iota$

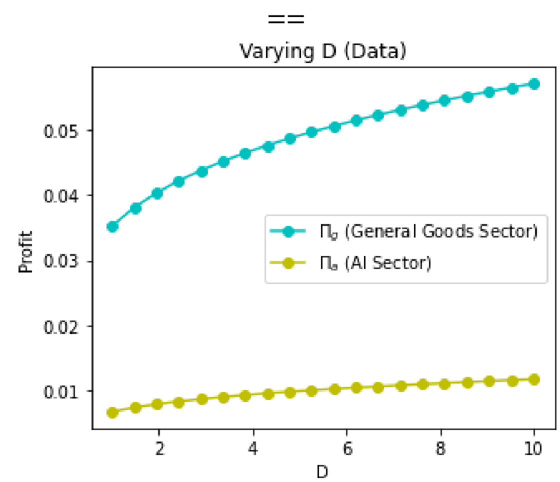


((d)) γ

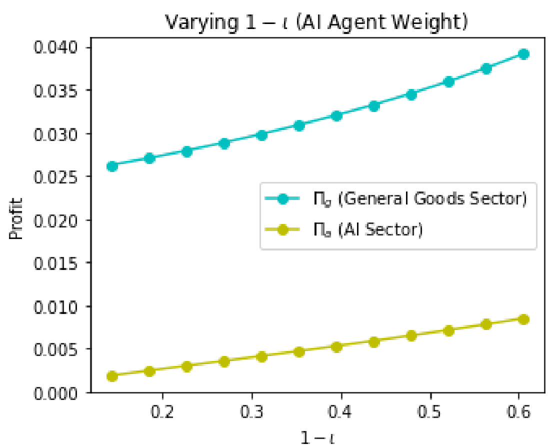
Figure III.4: Price of AI computation



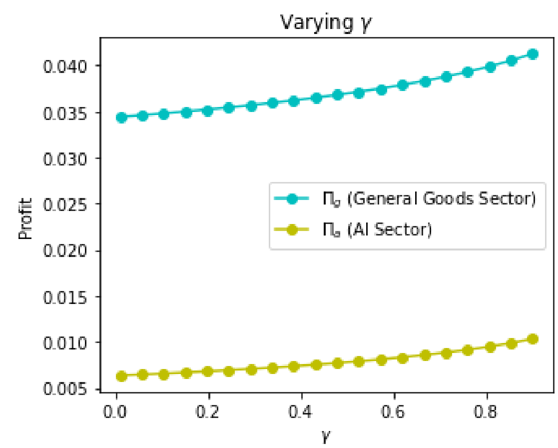
((a)) Z



((b)) D

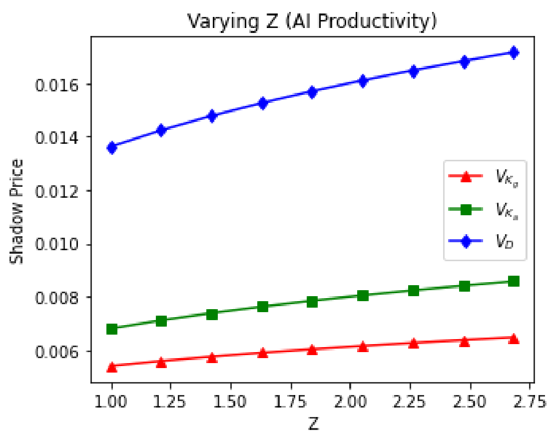


((c)) $1 - \iota$

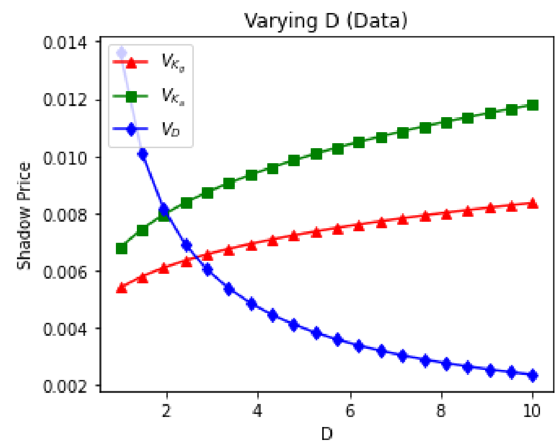


((d)) γ

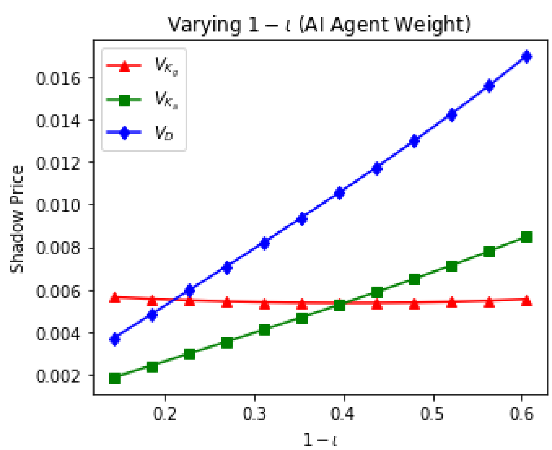
Figure III.5: Profits of Two Sectors



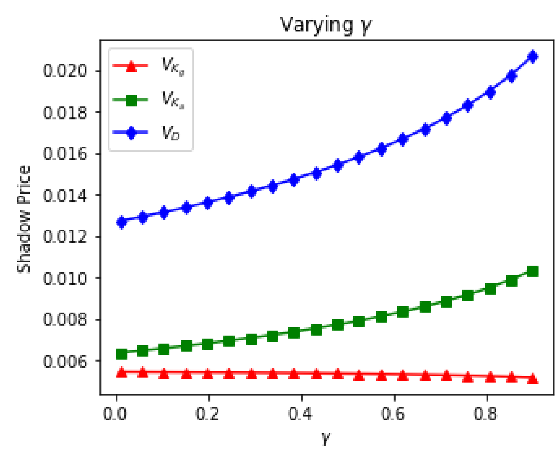
((a)) Z



((b)) D



((c)) $1 - \iota$



((d)) γ

Figure III.6: Prices of Capital and Data wages—our model generates precisely the same patterns. Specifically, an increase in γ raises the shadow prices of data D and the capital of the AI sector, increases profitability in both the AI and general goods sectors, drives wages downward, and reduces aggregate labor demand. Notably, the decline in labor demand within the larger general goods sector more than offsets any gains in AI-sector employment.

Beyond these empirical observations, our model predicts an additional phenomenon: the price of AI computation increases after the release of GPT 3.5. This outcome comes from the partial "training" barter Baley and Veldkamp (2025), in which users effectively "pay" for AI services with their feedback during the Reinforcement Learning from Human Feedback (RLHF) stage. As the number of ChatGPT users increases, so does the demand for AI computations, putting upward pressure on its price. The mechanism is straightforward: A higher γ implies greater substitutability between AI agents ($\mathbb{L}$) and human labor (L_g). As a result, firms in the general goods sector purchase more AI computation to replace costlier human labor, raising AI-sector profits and dampening overall wage and employment levels. Because these effects are monotonic in γ, greater exposure to AI - that is, larger γ - naturally entails higher AI computation prices, greater profitability, lower wages, and reduced job postings.

Analysis of Figure Varying Z (Algorithm Improvement)

Improvements in Z imply that the AI sector requires fewer inputs to produce a given level of AI computation. With the increases of AI productivity, general goods sector adopt more AI agent related to total labor input $\frac{\mathbb{L}}{\mathbf{L}}$. The production and profits of general goods sector, in consequence, go up as general goods sector adopt more AI agent as labor input at a lower cost. These results align with Babina et al. (2024) which suggests that firms that utilize AI tend to experience faster growth in sales, productivity and profits.

Unlike changes in γ, these changes in Z do not significantly affect labor demand. However, the shadow price of data increases at a lower rate as the slope of V_D w.r.t Z is decreasing, suggesting that general goods firms will invest less aggressively in collecting structured data and hiring data scientists when Z increases. This align with the crowd-out effect showed in our dynamic model.

Our model is also consistent with the model and empirical findings of Hampole et al. (2025), who identify declines in the price of intangible capital as the technological improvement that typically reduces wages and labor demand while boosting overall production. In our framework, these declines in the price of intangible capital map to reductions in the prices of AI computation, driven by AI productivity gains. Consequently, the labor demand in the general goods sector contracts even as output in that sector rises. In this way, our varying-Z model replicates the economic patterns that Hampole et al. (2025) and Acemoglu (2025) highlight.

Analysis of Figure Varying D

We next examine the impact of AI adoption on economy, where AI adoption is measured by the availability of data for AI computation or the number of data scientists who facilitate the use of Generative AI. In our model, this is captured by the data process D. Several key observations emerge. First, as D increases, the labor allocated to traditional goods production L_g decreases, indicating a reallocation of human resources to AI-related activities. Second, the profitability of both the general goods and AI sectors increases with D, underscoring the economic gains associated with investments in data science and AI capabilities. Finally, the price p and the wage w increase alongside D, reflecting the higher value of labor and the final product when advanced AI technologies are fully integrated into production processes.

III.c. Empiricial Study

We have seen in the static simulation that the change of γ and Z drives the economy to a new equilibrium. We could test if the real world behaves like our model. Our model is not limited to LLM but we are focusing on Chat GPT for now. The advent of GPT 3.5 in November 2022 is a huge event. It can be viewed as the change of γ, the elasticity of the substitute. After GPT 3.5, each version of GPT could be reviewed as a result of the increase in γ. Furthermore, the DeepSeek shock could be reviewed as an increase in Z. However, the DeepSeek shock is relatively new and the only variable we can observe is stock prices. When γ increases, in the last subsection we show that productivity, profitability, wage, shadow price, labor allocation, and other economic variables change accordingly. Empirically, we could do casual inference to see whether it is true in the real world by doing a random discontinuity test. After that, we could calibrate our static model parameters using the moment conditions at the break point.

IV. Dynamic Equilibrium Model

We build a general equilibrium model to investigate the role of AI productivity improvement, investment in data, and investment on capital on asset prices in AI economy. Solving the planner's problem is sufficient when the second welfare theorem holds. This model has three dynamics, which are (1) capital of the general goods sector; (2) capital of AI sector; (3) data or knowledge storage in the general goods sector.

IV.a. Households

There exists a continuum of identical households that maximize recursive utility V_t over sequences of consumption $C_{t:\infty}$ and leisure $N_{t:\infty}$. The Epstein-Zin preference in continuous time is defined by

$$V_t = \left[\delta \int_0^\infty \exp(-\delta\tau) \left(C_{t+\tau} N_{t+\tau}^{\psi}\right)^{1-\rho} d\tau\right]^{\frac{1}{1-\rho}}. \tag{6}$$

We solve the special case where $\rho = 1$, where the recursive preference becomes time separable:

$$V_t = \delta \int_0^\infty \exp(-\delta\tau) \log\left(C_{t+\tau} N_{t+\tau}^{\psi}\right) d\tau. \tag{7}$$

IV.b. AI Sector

The AI sector provides X_t units of AI computations to general goods sector for production using sector specific capital $K_{a,t}$ and labor $L_{a,t}$

$$X_t = Z K_{a,t}^{\alpha} L_{a,t}^{1-\alpha}. \tag{8}$$

We assume that AI productivity shocks are exogenous. A positive AI productivity shock means that the AI sector could provide more AI computations given the same amount of labor and capital. Instead of modeling Z_t as a dynamic, we merge the randomness of AI productivity into the capital process $K_{a,t}^{\alpha}$.

The stock of productive capital $K_{a,t}$, following conventional asset pricing setting, evolves as

$$dK_{a,t} = K_{a,t}\left(-\mu_a + \frac{I_{a,t}}{K_{a,t}} - \frac{\kappa_a}{2}\left(\frac{I_{a,t}}{K_{a,t}}\right)^2\right) dt + K_{a,t}\sigma_a dW_t^a. \tag{9}$$

The new investment $I_{a,t}$, increases the capital stock $K_{a,t}$, subject to an adjustment cost captured by the curvature parameter κ_a. The shock to AI capital contains both capital quality shock and technology shock.

AI sector sells AI computation at a competitive price p_t and hire labor at wage w_t to maximize their market value:

$$S_{a,t} = E_t \int_t^{\infty} \frac{\pi_s}{\pi_t} \left(p_s Z K_{a,s}^{\alpha} L_{a,s}^{1-\alpha} - w_s L_{a,s} \right) ds \tag{10}$$

IV.c. General goods Sector

The general goods sector produces consumption goods Y_t with three factors, sector specific capital $K_{g,t}$, human labor $L_{g,t}$, and AI agent $\mathbb{L}_t$ following the Cobb-Douglass technology. All production is used for consumption, investment in capitals of two sectors, and investment in data:

$$AK_{g,t}^{\beta}[\iota L_{g,t}^{\gamma} + (1-\iota)\mathbb{L}_t^{\gamma}]^{\frac{1-\beta}{\gamma}} = C_t + I_{g,t} + I_{a,t} + I_{D,t}. \tag{11}$$

We assume that the total productivity factor A is constant. The stock of productive capital, K_t, evolves as

$$dK_{g,t} = K_{g,t} \left(-\mu_g + \frac{I_{g,t}}{K_{g,t}} - \frac{\kappa_g}{2} \left(\frac{I_{g,t}}{K_{g,t}} \right)^2 \right) dt + K_{g,t}\sigma_g dW_t^g, \tag{12}$$

which is similar to the AI sector capital evolution.

We treat the data as the by-product of production following Farboodi and Veldkamp (2021). The process of data D_t captures the stock of knowledge or data and evolves as

$$dD_t = -\zeta D_t dt + \psi_0 \left(\frac{I_{D,t}}{D_t} \cdot \frac{Y_t}{D_t} \right)^{\psi_1} D_t dt + \sigma_D D_t dW_t^D, \tag{13}$$

where $0 < \psi_1 < 1$ captures spillover effects of data. Our setting is the continuous extension of Section 9.1 in Baley and Veldkamp (2025). The investment in data $I_{D,t}$ is the endogenized "data savviness" that measures the eagerness to collect data from production activities, and $\frac{Y_t}{D_t}$ characterizes the data feedback loop and the "by-product" feature that data can be perceived. While we will solve a social planner's problem, this evolution equation potentially includes an externality associated with non-rivalry property. The term $\sigma_r dW_t$ reflects an exogenous stochastic inflow of information about the future likelihood of a technological advance. In each period, firms hire labor at wage w_t and purchase AI computation to maximize their value

$$S_{g,t} = E_t \int_t^{\infty} \frac{\pi_s}{\pi_t} \left(A K_{g,s}^{\beta} [\iota L_{g,s}^{\gamma} + (1-\iota)\mathbb{L}_s^{\gamma}]^{\frac{1-\beta}{\gamma}} - w_s L_{g,s} - p_s X_s \right) ds. \tag{14}$$

A common practice in the literature on production-based asset pricing is the AK production function, where capital is interpreted broadly and incorporates human capital, organizational capital, and intangible assets Hansen et al. (2024). However, we separate labor and data from capital because labor allocation and data usage are two key features in AI economy different from the Industrial Revolution.

V. Model Solution

V.a. Social Planner's Problem

In the two sector AI economy model, we define three state variables:

$$\{\widehat{K}_{g,t}, \widehat{K}_{a,t}, \widehat{D}_t\}, \tag{15}$$

where the variable with hat means logarithm of that variable. Three inter-temporal choices are three investments in capitals and data and two labor allocation choices

$$\{\frac{I_{g,t}}{K_{g,t}}, \frac{I_{a,t}}{K_{a,t}}, \frac{I_{D,t}}{K_{g,t}}\}, \{L_{g,t}, L_{a,t}\}. \tag{16}$$

When $\rho = 1$, the HJB equation planner solves is

$$\begin{aligned}
0 \;=\; & \max_{\frac{I_{g,t}}{K_{g,t}}, \frac{I_{a,t}}{K_{a,t}}, \frac{I_{D,t}}{K_{g,t}}, L_{g,t}, L_{a,t}} \quad \delta \log \left(A K_{g,t}^{\beta} [\iota L_{g,t}^{\gamma} + (1-\iota)\mathbb{L}_t^{\gamma}]^{\frac{1-\beta}{\gamma}} - I_{g,t} - I_{a,t} - I_{D,t} \right) + \psi \log N_t - \delta V \\
& + \frac{\partial V_t}{\partial \widehat{K}_{g,t}} \left(-\mu_g + \frac{I_{g,t}}{K_{g,t}} - \frac{\kappa}{2} \left(\frac{I_{g,t}}{K_{g,t}} \right)^2 - \frac{\sigma_g^2}{2} \right) + \frac{\partial^2 V_t}{\partial \widehat{K}_{g,t} \partial \widehat{K}'_{g,t}} \frac{|\sigma_g|^2}{2} \\
& + \frac{\partial V_t}{\partial \widehat{K}_{a,t}} \left(-\mu_a + \frac{I_{a,t}}{K_{a,t}} - \frac{\kappa}{2} \left(\frac{I_{a,t}}{K_{a,t}} \right)^2 - \frac{\sigma_a^2}{2} \right) + \frac{\partial^2 V_t}{\partial \widehat{K}_{a,t} \partial \widehat{K}'_{a,t}} \frac{|\sigma_a|^2}{2} \\
& + \frac{\partial V_t}{\partial \widehat{D}_t} \left(-\zeta + \psi_0 \left(\frac{I_{D,t}}{K_{g,t}} \frac{K_{g,t}}{D_t} \frac{Y_t}{D_t} \right)^{\psi_1} - \frac{\sigma_D^2}{2} \right) + \frac{\partial^2 V_t}{\partial \widehat{D}_t \partial \widehat{D}'_t} \frac{|\sigma_D|^2}{2}
\end{aligned}$$

First order condition of inter-temporal decisions:

$$\frac{\partial V_t}{\partial \widehat{K}_{g,t}}\left(1-\kappa\frac{I_{g,t}}{K_{g,t}}\right)=\delta\frac{K_{g,t}}{C_t}, \tag{17}$$

$$\frac{\partial V_t}{\partial \widehat{K}_{a,t}}\left(1-\kappa\frac{I_{a,t}}{K_{a,t}}\right)=\delta\frac{K_{a,t}}{C_t}, \tag{18}$$

$$\psi_0\psi_1\frac{\partial V_t}{\partial \widehat{D}_t}\left(\frac{I_{D,t}}{K_{g,t}}\right)^{\psi_1-1}\left(\frac{K_{g,t}}{D_t}\cdot\frac{Y_t}{D_t}\right)^{\psi_1}=\delta\frac{K_{g,t}}{C_t}. \tag{19}$$

V.b. Household FOC

The decision about the labor supply of households is intratemporal and depends on current consumption C_t and wage w_t. The optimal leisure time is to set the FOC of the value function with respect to N_t equal to zero. The first-order derivative of consumption w.r.t. labor supply is wage.

$$1-L_{g,t}-L_{a,t}=N_t=\psi\frac{C_t}{w_t} \tag{20}$$

V.c. General Goods Sector FOC

General Goods sector decide how much AI computation to use in production. The FOC is intratemporal:

$$Y_t\cdot(1-\beta)(1-\iota)(1-\theta)\left(\frac{\mathbb{L}_t}{\mathbf{L}_t}\right)^{\gamma}X_t^{-1}=p_t. \tag{21}$$

Labors are hired at a competitive wage w_t. The FOC w.r.t wage is

$$Y_t\cdot(1-\beta)\iota\left(\frac{L_{g,t}}{\mathbf{L}_t}\right)^{\gamma}L_{g,t}^{-1}=w_t, \tag{22}$$

$$(1-\alpha)p_tX_tL_{a,t}^{-1}=w_t. \tag{23}$$

VI. Asset Prices

VI.a. Stochastic Discount Factor

For log utility, the stochastic discount factor is

$$\pi_t = \exp(-\delta t)\delta \left(C_t N_t^{\psi}\right)^{-1}. \tag{24}$$

The SDF can be written as

$$\frac{d\pi_t}{\pi_t} = -r_{f,t}dt - \lambda_{a,t}dW_t^a - \lambda_{g,t}dW_t^g - \lambda_{D,t}dW_t^D, \tag{25}$$

where

$$\lambda_{g,t} = \beta\frac{Y_t}{C_t}\sigma_g, \tag{26}$$

$$\lambda_{a,t} = \alpha\gamma(1-\rho)(1-\iota)(1-\beta)\left(\frac{\mathbb{L}_t}{\mathbf{L}_t}\right)^{\gamma}\frac{Y_t}{C_t}\sigma_a, \tag{27}$$

$$\lambda_{D,t} = \rho(1-\iota)(1-\beta)\left(\frac{\mathbb{L}_t}{\mathbf{L}_t}\right)^{\gamma}\frac{Y_t}{C_t}\sigma_D, \tag{28}$$

and the risk free rate is

$$r_{f,t} = \delta + \frac{1}{2}\frac{Y_t}{C_t}\beta^2\sigma_g^2 \tag{29}$$

$$+\frac{1}{2}\frac{Y_t}{C_t}(1-\beta)(1-\iota)\left(\frac{\mathbb{L}_t}{\mathbf{L}_t}\right)^{\gamma}\left[\iota\left(\frac{L_{g,t}}{\mathbf{L}_t}\right)^{\gamma} + (1-\beta)(1-\iota)\right] \tag{30}$$

$$\cdot\left[\rho^2\sigma_D^2 + \alpha^2\gamma^2(1-\rho)^2\sigma_a^2\right] \tag{31}$$

We got the same results aligning with the interest rate observation given by Chow et al. (2024) . When AI replaced more human labor in the general goods sector or human labor becomes easier to substitute by AI, the real interest rate increases as $\frac{Y_t}{C_t}$, $\frac{\mathbb{L}_t \cdot L_{g,t}}{\mathbf{L}_t^2}$ and γ increases.

VI.b. Sector Valuation

The firm chooses the optimal investment to maximize the firm's values. The Euler equation is

$$0 = \pi_t \Pi_{i,t} dt + E_t[d(\pi_t S_{i,t})], \tag{32}$$

where

$$\frac{1}{\pi_t}E_t[d(\pi_t S_{i,t})] = E_t[S_{i,t}\frac{d\pi_t}{\pi_t} + dS_{i,t} + \frac{d\pi_t}{\pi_t}dS_{i,t}] \tag{33}$$

$$= [-r_f S_{i,t} - \lambda_{a,t}\sigma_a \frac{\partial S_{i,t}}{\partial \widehat{K}_{a,t}} - \lambda_{g,t}\sigma_g \frac{\partial S_{i,t}}{\partial \widehat{K}_{g,t}} - \lambda_{D,t}\sigma_D \frac{\partial S_{i,t}}{\partial \widehat{D}_t} \tag{34}$$

$$+ \frac{\partial S_{i,t}}{\partial \widehat{K}_{g,t}}\left(-\mu_g + \frac{I_{g,t}}{K_{g,t}} - \frac{\kappa}{2}\left(\frac{I_{g,t}}{K_{g,t}}\right)^2 - \frac{\sigma_g^2}{2}\right) + \frac{\partial^2 S_{i,t}}{\partial \widehat{K}_{g,t}\,\partial \widehat{K}'_{g,t}}\frac{|\sigma_g|^2}{2} \tag{35}$$

$$+ \frac{\partial S_{i,t}}{\partial \widehat{K}_{a,t}}\left(-\mu_a + \frac{I_{a,t}}{K_{a,t}} - \frac{\kappa}{2}\left(\frac{I_{a,t}}{K_{a,t}}\right)^2 - \frac{\sigma_a^2}{2}\right) + \frac{\partial^2 S_{i,t}}{\partial \widehat{K}_{a,t}\,\partial \widehat{K}'_{a,t}}\frac{|\sigma_a|^2}{2} \tag{36}$$

$$+ \frac{\partial S_{i,t}}{\partial \widehat{D}_t}\left(-\zeta + \psi_0\left(\frac{I_{D,t}}{K_{g,t}}\frac{K_{g,t}}{D_t}\frac{Y_t}{D_t}\right)^{\psi_1} - \frac{\sigma_D^2}{2}\right) + \frac{\partial^2 S_{i,t}}{\partial \widehat{D}_t\,\partial \widehat{D}'_t}\frac{|\sigma_D|^2}{2}]dt. \tag{37}$$

The dividends of two sectors are

$$\Pi_{g,t} = AK_{g,t}^{\beta}[\iota L_{g,t}^{\gamma} + (1-\iota)\mathbb{L}_t^{\gamma}]^{\frac{1-\beta}{\gamma}} - w_t L_{g,t} - p_t X_t, \tag{38}$$

$$\Pi_{a,t} = p_t Z K_{a,t}^{\alpha} L_{a,t}^{1-\alpha} - w_t L_{a,t}. \tag{39}$$

VI.c. Example Economy

We plot the impulse responses on the productivity shock in the AI sector. For simple illustration, we adopt the processes from the existing asset pricing literature. The subjective discount rate is set to $\delta = 0.01$. Capital processes are aligned with Barnett et al. (2024):

$$\mu_g = 0.035, \quad \kappa_g = 7, \quad \sigma_g = 0.01,$$

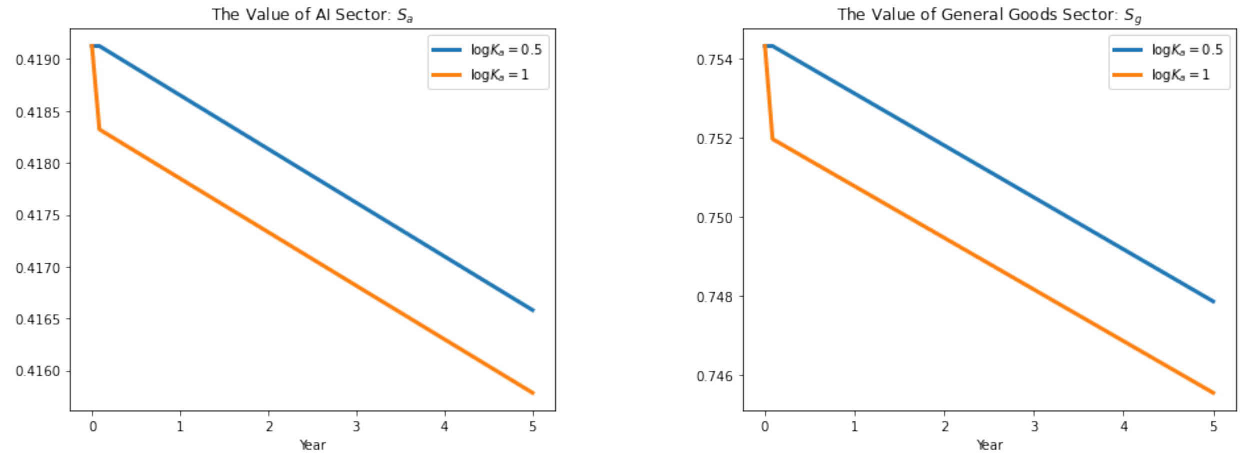
and for the data process we use

$$\zeta = 0, \quad \psi_0 = 0.1, \quad \psi_1 = 0.5, \quad \sigma_D = 0.0078.$$

Furthermore, reflecting that the capital of the AI-sector depreciates more quickly compared with the general goods sector, we set

$$\mu_a = 0.05, \quad \kappa_a = 6, \quad \sigma_a = 0.01.$$

These parameterizations serve as our baseline calibration; we plan to refine or formally calibrate them in future work.



((a)) $S_{a,t}$: Value of AI sector

((b)) $S_{g,t}$: Value of General Goods Sector

Figure VI.1: Simulated values for the two sectors.

We set the simulation starting values to $\widehat{K}_{g,0} = 2$ and $\widehat{D}_0 = 0.1$. In order to show the impact of the AI productivity shock, we set $\widehat{K}_{a,0} = \{0.5, 1\}$ to see the difference between two simulations.

Positive productivity shocks can decrease the value of the AI sector and the general goods sector shown in the figure (VI.1). The improvement in productivity causes overcapacity and affects the firm values of the AI sector aligned with Jensen (1986).

Our numerical results explain the recent DeepSeek shock, which is major algorithmic breakthroughs that reduce the cost of AI training. Following the launch of DeepSeek R1, the value of the AI sector declined – for example, the price of NVIDIA's stock fell around 20%. By lowering training expenses, these shocks can initially appear beneficial for the AI sector; however, our analysis suggests that firm values in the AI sector may actually decline substantially, as lower entry barriers and increased competition may erode future profitability. The general goods sector experiences only a modest reduction in firm value due to its comparatively indirect exposure to AI innovation.

Meanwhile, the decline in AI computation costs stimulates hiring in the AI sector at the expense of traditional production, resulting in a short-term boost in overall labor demand as workers shift from general goods to AI-related tasks. A positive shock to AI productivity crowds out data investment in the general goods sector. As firms become more efficient with AI, they allocate fewer resources to data, which slows the pace of data accumulation.

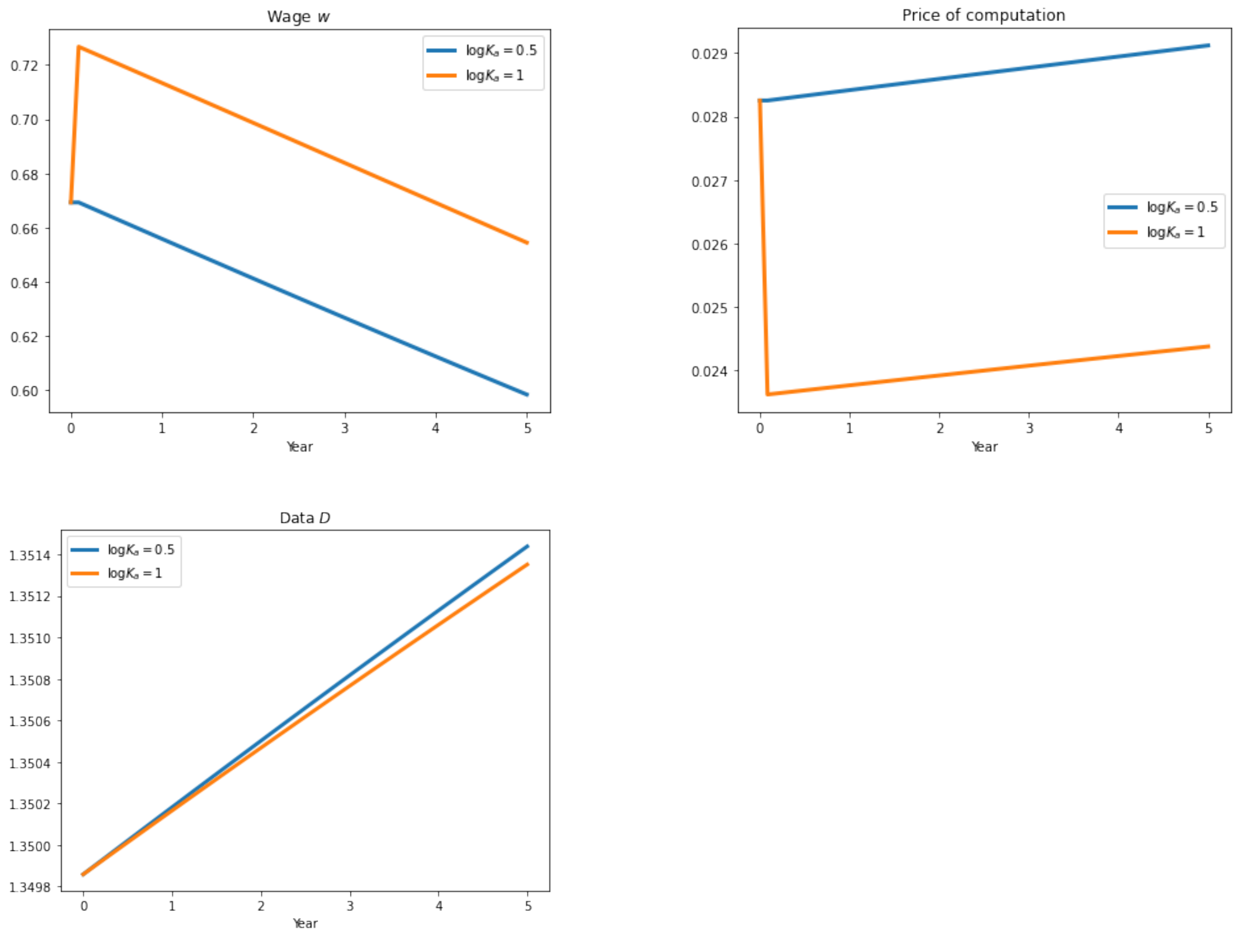


Figure VI.2: Competitive wage, price of AI computation, and data.

VII. Conclusion

Our analysis underscores that AI's impact on the economy transcends mere technological progress and profit optimization. Through the lens of viewing AI as a distinct factor of production, combining advanced computation and specialized data, we capture both the efficiency gains and the profound structural shifts that emerge when AI-based labor partially displaces human labor. This framework is utilized to quantitatively understand its broader consequences, particularly for labor markets, data usage, and valuations across sectors.

A central takeaway is that increases in AI efficiency, while potentially catalyzing higher overall productivity, can paradoxically erode long-term valuations. Our finding suggests that intensified competition in the AI sector appears to flatten or even reverse the expected gains in firm value, revealing that technology-driven expansions may create fertile ground for overinvestment or unsustainable price dynamics. Meanwhile, the valuations of the general goods sector exhibit greater resilience precisely because their exposure to AI disruptions is indirect. This interplay highlights the importance of modeling cross-sector feedback loops rather than assessing each sector in isolation.

Our results also shed light on the effects of the labor market. On the one hand, a rapid surge in AI capabilities can raise wages by reallocating workers to high-demand activities, echoing the idea that complementary labor skills, particularly around data science, remain scarce resources. On the other hand, if the AI capacity for replace human labor becomes too powerful, wages can be suppressed, especially for tasks that become rapidly automatable. These complex labor dynamics reflect the delicate balance between the continued relevance of human capital and the disruptive potential of AI.

Our exploration of 'DeepSeek shocks', sudden breakthroughs that dramatically lower AI training costs, reveals that short-term efficiency gains may come at the expense of dampening future investment in data quality and related infrastructure. As computation becomes cheaper and more powerful, firms may find structured data less urgent, thereby reshaping how resources are allocated across production activities.

In summary, our theoretical framework clarifies how AI's transformative role in production extends beyond efficiency to shape wage trajectories, asset valuations, and data investment. These results can guide policymakers and stakeholders in anticipating the ripple effects of emerging AI capabilities. Ultimately, navigating the ongoing integration of AI into society requires a holistic view that reconciles efficiency with equity, ensuring that innovative progress does not inadvertently exacerbate labor market inequalities or undermine the resilience of diverse economic sectors.

VIII. Appendix

A. Neural Nets Implementations

We apply the deep Galerkin method - policy improvement algorithms (DGM-PIA) to solve the nonlinear HJB equation with FOCs following Barnett et al. (2023). There are intratemporal FOCs that are unique in our model settings, and we add those FOCs into the loss function of the control iteration steps. For the networks used to approximate both the value functions and the optimal controls, we use feedforward neural networks with 4 hidden layers of width 32 and `tanh` activation function for hidden layers and `sigmoid` for the output layer. To train the neural nets, we run 200000 epochs with a batch size of 32. The learning rates are $40e^{-5}$ and we use the ADAM optimizer proposed in Kingma and Ba (2014). For more details, visit our GitHub repository at GitHub Repository.

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